Departamento de Estructura Económica

Innovation behaviour and performance in Ecuadorian firms

DOCTORAL DISSERTATION

Author:

Jorge Antonio Rodríguez Moreno

Supervisor:

María Engracia Rochina Barrachina

Doctorado en Economía Industrial

Febrero 2018

Contents

List of Tables

List of Figures

List of Appendixes

AGRADECIMIENTOS

En primera instancia quisiera agradecer a Dios por permitirme completar una etapa más en este transitar académico. También, quiero hacer una mención especial a María Rochina Barrachina mi directora de tesis, quien ha sido una guía durante todos mis años de estudio en la Universidad de Valencia y que sin su apoyo este trabajo no habría podido lograrse. Además, a los directores del departamento de Estructura Económica entre los años 2014 y 2018 (Cecilio Tamarit y Salvador Gil respectivamente), quienes me brindaron todas las facilidades durante cada una de las estancias en la Universidad de Valencia. A los directivos de la Universidad Técnica Federico Santa María, Campus Guayaquil el Dr. Roberto Hanze, el Ing. Fernando Maldonado, la Ing. Ketty García y el Lcdo. Anastasio Gallego quienes depositaron su confianza y apoyo irrestricto durante mi etapa de estudios en Valencia. Así también agradezco a los profesores María Rochina, Juan Sanchis, Amparo Sanchis, Pilar Beneito, Juan Máñez, Andrés Picazo, José Sempere, Rafael Moner, Mercedes Beltrán, quienes con sus clases y/o consejos han contribuido en mi formación académica y personal en algún momento de este camino por España. Además, al profesor Leonel Corona por permitirme hacer una estancia en el centro de investigación que dirige en la ciudad de México.

Desde lo personal, agradezco a mis padres (José y Narcisa) quienes me han permitido entender la importancia de los sacrificios propios de la educación. A mi abuelita María que es el motor que mueve a mi familia y su vida es una enseñanza diaria. A mis hermanos (Juan Carlos y José Xavier) les agradezco ser mi motivación principal para culminar esta etapa. A mi familia (Piero, Pamela, Christian, Felipe, César, Alejandro, Carlos, Alejandro, Mike, mis tíos César, Carlos, Pocha, Lucho) quienes siempre

tuvieron una palabra de ánimo cuando más duro se mostraba el camino propio de la distancia. A mis amigos/hermanos que me ha dado el destino (Gaby, Carito, Henrry, Alfredo, Johanna, Fanny, Elizabeth) quienes todo este tiempo han estado pendiente de mí a nivel personal a pesar de los constantes viajes y las largas estancias. Agradezco también a esas personas que me han permitido en estos años en Valencia sentir el calor de una familia (Sole, Carlos Isa, Ainhoa, Gaby, Alex, Marcela y Luis) y son quienes han podido ayudarme en más de una ocasión en cada una de mis estancias. A mis compañeros del doctorado (Luis, Rubén, Ernesto, Adriana, Mariola, Adri, Paula, Jesús, Marta, Carlos, Laura, Eli, Danny) quienes en diferentes momentos fuimos apoyo mutuo en los duros momentos de los estudios doctorales, y a los de compañeros/amigos en Ecuador (Francisco y Andrés) quienes supieron darme una mano en más de una ocasión para venirme a España. A Marta, mi compañera y amiga durante todo el doctorado con quien compartimos no solo conocimientos, sino también miedos, frustraciones y alegrías en tertulias interminables que hicieron más llevaderos nuestros días en Valencia.

El terminar el doctorado no solo deja el conocimiento académico, en un departamento dónde se respira ciencia económica al más alto nivel, sino también conocer a gente que marca de alguna forma tu vida.

RESUMEN

Hay una serie de cuestiones que introducimos a continuación y que justifican el interés del contenido de esta Tesis para un país como Ecuador. Las mismas tienen que ver con la situación económica del país y sus objetivos a la hora de acercar esta economía en desarrollo a economías de mayor liderazgo en cuestiones relacionadas con la modernización de su tejido productivo como motor para el crecimiento económico, el fomento de unas exportaciones de productos más competitivos y la difusión de la tecnología entre las empresas que lo conforman.

En particular, la economía ecuatoriana aún depende en gran medida de los precios del petróleo y de la agricultura. Las exportaciones del sector primario representan más del 80% de las exportaciones totales (United Nations, 2013). El gobierno ecuatoriano está muy interesado en transformar la economía de un modo más orientado al conocimiento. Sin embargo, poco se sabe en este país sobre los efectos que las actividades de innovación tienen en los resultados de las empresas, de modo que se puedan implementar en las mejores condiciones posibles determinadas políticas públicas encaminadas a mejorar la situación competitiva de las empresas a través de la innovación. Desde 2013, Ecuador ha estado tratando de mejorar su estructura productiva. En particular, el objetivo número 10 del Plan Nacional de Desarrollo SENPLADES (2013) explicaba los problemas del sector industrial en Ecuador, especialmente los problemas del sector manufacturero. Las exportaciones manufactureras ecuatorianas representaban en promedio 8,9% de las exportaciones totales (World Bank, 2013) y, de ellas, las exportaciones con contenido altamente tecnológico representaban, en promedio, el 5,5% (United Nations, 2013). Por otro lado, las importaciones manufactureras representaban, en promedio, el 74,79% de las

importaciones totales. El desequilibrio global entre las exportaciones manufactureras y las importaciones se convirtió en algo aún más problemático para la economía desde el año 2000, cuando Ecuador adoptó el dólar estadounidense (USD) como su moneda local y perdió con ello la autonomía de su política monetaria. En cuanto a la innovación, la situación de la economía no era mejor. Así, por ejemplo, en 2008, la ratio de inversión en I+D sobre el PIB fue de tan sólo el 0,25% (Instituto de Estadística, 2011). Por lo tanto, si se combina la situación de las exportaciones y de la innovación en el país, el interés del gobierno ecuatoriano con el Objetivo 10 del Plan Nacional de Desarrollo SENPLADES (2013) era el establecimiento de políticas públicas para modificar las estructuras productivas y promover la competitividad de la industria a través de actividades de innovación.

Con estos propósitos, el primer paso dado por el gobierno ecuatoriano fue conocer en mayor profundidad y caracterizar la estructura productiva ecuatoriana mediante la recopilación de información microeconómica sobre las empresas del país. Esto se llevó a cabo mediante la elaboración de un Censo Económico Nacional en 2010, Censo que abarca todo el universo de empresas ecuatorianas. El Censo fue realizado por el Instituto Ecuatoriano de Estadísticas y Censos (INEC). Este es el último censo económico de Ecuador disponible e incluye 511.130 empresas de todos los sectores productivos de la economía. Incluye información sobre características de las empresas como, por ejemplo: su edad, ubicación, estado legal, sector industrial, empleo, ventas y clientes principales, costes, ingresos y activos fijos, y algunas actividades de innovación como son las inversiones en I+D o en la capacitación de los trabajadores y el uso de las TICs.

El Capítulo 2 de esta Tesis usa precisamente el universo de empresas manufactureras en el Censo Económico de Ecuador (2010) para estudiar la relación existente entre las actividades de innovación de las empresas y la productividad y los márgenes de ganancia de las mismas. Se supone que un motor clave para la productividad es la innovación. Además, tanto la innovación como la productividad pueden afectar la capacidad de las empresas para establecer precios por encima de los costes marginales. Como actividades innovadoras, consideramos las inversiones en I+D y las inversiones en formación de los trabajadores, así como el uso de las TICs. Si estas inversiones son importantes para la productividad y la capacidad de las empresas a la hora de establecer mayores márgenes de beneficios, entonces se transforman en cuestiones de interés a tener en cuenta en las políticas de desarrollo de países en vías de desarrollo. Sin embargo, si esto es así, resulta curioso que, si utilizamos el último Censo Económico del Ecuador y sus datos para empresas manufactureras, el 88,34% de ellas no están implicadas en ninguna de las tres actividades de innovación consideradas. Todo esto pone de relieve que las empresas manufactureras ecuatorianas aún no han obtenido todos los beneficios potenciales que se derivan del ejercicio de actividades de innovación. La escasa utilización de esta base de datos para un análisis empírico no meramente descriptivo, hace que este trabajo sea novedoso y pionero para Ecuador.

En este sentido, entendiendo que la creación de conocimiento es multidimensional, nuestros objetivos en este Capítulo son múltiples. En primer lugar, nos interesa explicar la probabilidad de las empresas de llevar a cabo actividades de I+D, formación de los trabajadores y uso de las TICs. La probabilidad de estas actividades requerirá la estimación de un modelo probit trivariante teniendo en cuenta la posible interrelación entre ellas. En segundo lugar, también estamos interesados en explicar los determinantes que en las empresas potencian la decisión de llevar a cabo I+D y la intensidad con la que realizan esta inversión, así como estas mismas cuestiones en relación a las inversiones que realizan en formación de sus trabajadores.

Lamentablemente, la base de datos no tiene información sobre los gastos en TICs. Los problemas de selección de muestra que aparecen cuando se trata de explicar el esfuerzo innovador en I+D y en formación de la mano de obra, se toman en consideración por medio de la estimación de modelos de Heckman bivariantes de selección de muestra. En tercer lugar, introducimos estimaciones de etapas previas en pasos posteriores dentro del marco del modelo de Crépon-Duguet-Mairesse (CDM, 1998) para estudiar los vínculos existentes entre las actividades de innovación y la productividad de las empresas. Hacemos esto mediante el empleo de medidas alternativas de productividad tales como la productividad del trabajo y la productividad total de los factores (PTF en lo sucesivo). Esta última medida de productividad se obtiene tanto partiendo de funciones de producción Cobb-Douglas como de funciones Translog. Finalmente, verificamos si las actividades de innovación no solo afectan a la productividad de las empresas, sino que también influyen en la capacidad de las mismas para establecer precios por encima de sus costes marginales y, por lo tanto, afectan a sus márgenes de beneficio. Los márgenes de beneficio de las empresas se estiman a partir de las estimaciones procedentes de la función de producción de las mismas. La implementación de un enfoque CDM permite tomar en consideración la existencia de posibles problemas de endogeneidad de las variables de innovación en las ecuaciones de productividad y de márgenes de beneficio. Esto se realiza por medio del uso de funciones de control (véase Wooldridge, 2010).

Las novedades en este Capítulo frente a la literatura relacionada existente son las siguientes. En primer lugar, utilizamos una definición amplia de las actividades de innovación de las empresas que incluye inversiones en I+D y en formación de los trabajadores, así como el uso de las TICs. Se espera que esto contribuya a la minimización del sesgo de variables omitidas que podría de otro modo aparecer al tratar de comprender las consecuencias que para los resultados de las empresas tiene la decisión de realizar estas actividades innovadoras y el esfuerzo inversor en las mismas. En segundo lugar, vamos un paso más allá en el marco del modelo CDM al incorporar una segunda medida de resultados empresariales, sus márgenes de beneficios, además de la variable tradicional de productividad. Por lo tanto, no solo vamos a responder a la pregunta sobre qué variables determinan las decisiones de innovación y el esfuerzo innovador de las empresas, para luego más tarde analizar sus efectos sobre la PTF, sino que también abrimos nuevos caminos para investigar el papel de las actividades de innovación y la PTF sobre los márgenes de beneficio empresarial. En tercer lugar, con la etapa final de nuestro procedimiento de estimación en el Capítulo, podemos distinguir, condicionando al valor de la PTF en la regresión de los márgenes de beneficios, si el efecto de las variables de innovación en los citados márgenes opera a través de la eficiencia, es decir, de los costes marginales aproximados por la PTF y/o a través de la mayor capacidad de las empresas para establecer precios por encima de los costes marginales, ya que la innovación probablemente fomenta la producción de productos de mayor calidad. Finalmente, la literatura que integra todos estos elementos en un marco unificado es escasa y está principalmente relacionada con las economías desarrolladas. Por lo tanto, averiguar si este tipo de actividades tienen un papel relevante para los países en vías de desarrollo es de gran interés no solo para los gerentes de las empresas sino también para los gestores públicos, ya que este tipo de inversiones son fuentes importantes de productividad y capacidad para fijar mayores márgenes de beneficio. Estas cuestiones son importantes para las políticas de desarrollo a realizar en los países en vías de desarrollo. Además, este es el primer estudio de este tipo para Ecuador.

Los principales resultados en el Capítulo se pueden resumir de la siguiente manera. En primer lugar, la profesionalización y las buenas prácticas empresariales determinadas por la pertenencia a un grupo empresarial, tener acceso a financiamiento, realizar actividades de investigación de mercado, contabilidad y tener inquietudes medioambientales, explican unas mayores propensiones e intensidades de inversión en I+D y en capacitación de los trabajadores, así como un mayor uso de las TICs. En segundo lugar, las tres actividades de innovación consideradas afectan positivamente a la PTF y a los márgenes de ganancia de las empresas. En tercer lugar, parte del efecto de las actividades de innovación sobre los márgenes opera influyendo en los precios y no solo en la eficiencia. En cuarto lugar, detectamos la existencia de incentivos a innovar y de mayores márgenes que han sido impulsados por la presión de demanda. En quinto lugar, también detectamos cierta evidencia sobre el papel que el aprendizaje y los requisitos de calidad del producto debido a su venta en mercados internacionales ejerce en el fomento tanto de las innovaciones como de unos mayores precios. Finalmente, obtenemos resultados que pueden ser indicativos de la existencia de restricciones financieras que afectan a la innovación, atenuados en el caso de empresas que pertenecen a un grupo empresarial o que tienen acceso a financiamiento externo.

Esto demuestra claramente el importante papel que pueden tener las políticas públicas para fomentar la difusión de estas actividades entre las empresas con el fin de obtener efectos sólidos en las medidas de resultados de las mismas, tales como su productividad o sus beneficios empresariales. También hay espacio para la intervención del gobierno tratando de aliviar las restricciones financieras de las empresas manufactureras ecuatorianas que se enfrentan a la toma de decisiones relacionadas con las inversiones en innovación.

El segundo paso que el gobierno ecuatoriano tomó en la dirección de recolectar datos relevantes para diagnosticar la estructura productiva y el estado de la innovación en las empresas ecuatorianas, consiste en la realización de la Encuesta Nacional de

Actividades de Innovación de Ecuador (NIAS). Esta es una encuesta patrocinada por la Oficina Nacional de Estadísticas y Censos de Ecuador (INEC) y la Secretaría de Educación Superior, Ciencia, Tecnología e Innovación (SENESCYT). Se trataba de la primera vez que Ecuador realizaba una encuesta sobre las decisiones de innovación y los resultados a nivel de la empresa. La información en la encuesta corresponde a un período de tres años (2009-2011) y es bastante similar en estructura y variables a la proporcionada por las Encuestas de Innovación Comunitarias (CIS) para los países europeos. La encuesta abarca 2.815 empresas extraídas de la población en el último Censo Económico de Ecuador (2010), cubre todas las regiones del país y es representativa de los distintos estratos de tamaño de la industria. En la encuesta, NIAS incluye todo tipo de sectores siguiendo la clasificación de la CIIU Rev. 4 de las Naciones Unidas, excluyendo agricultura. Responder el cuestionario es obligatorio para las empresas.

En el Capítulo 3 de la Tesis, la principal fuente de información es NIAS. El objetivo principal aquí es el estudio de los efectos de la innovación en el crecimiento del empleo de las empresas. Consideramos cuatro tipos de innovaciones: innovaciones de producto, proceso, organización y marketing. Aplicamos la metodología desarrollada por Harrison *et al.* (2014) extendiéndola para incluir también innovaciones de marketing y organizativas. Además del objetivo central del Capítulo, también tenemos algunos objetivos suplementarios. En este sentido, estamos interesados en proporcionar alguna evidencia sobre el vínculo que existe entre los diferentes tipos de innovaciones y la composición de la fuerza de trabajo de la empresa en términos de calidad y salarios. Podemos considerar tanto las cualificaciones más altas como los salarios como indicadores de mayor calidad de la mano de obra requerida y creada por las empresas más innovadoras. Si este fuera el caso, no solo la innovación es social y

económicamente deseable porque genera crecimiento del empleo sino también porque podría ayudar a mejorar la calidad del empleo al afectar la composición de las cualificaciones de la mano de obra y sus salarios (primas salariales basadas en la tecnología). Por ejemplo, la innovación de producto puede aumentar la variedad y la calidad y, por lo tanto, puede conducir a la mejora de la cualificación de la mano de obra y contribuir al pago de salarios más altos. Si bien Ecuador no tiene una tasa de desempleo muy alta (5.23% durante el período analizado), sin embargo, sí tiene un alto porcentaje de empleo vulnerable (42.73% del empleo total). La vulnerabilidad laboral es un indicador para medir la calidad de los puestos de trabajo que fue destacado en los Objetivos del Milenio de las Naciones Unidas para 2015.

La mayor parte de la evidencia existente sobre los efectos de la innovación en el empleo proviene de estudios realizado para países desarrollados y, además, solo considera en gran medida los dos tipos de innovaciones contempladas en las ediciones del Manual de Oslo anterior a la de 2005 (es decir, innovaciones de producto y de proceso). Sin embargo, es interesante destacar que nuestro trabajo es el primero que considera a las innovaciones de marketing como un tipo diferenciado de innovación que debe considerarse por separado en el contexto del modelo de Harrison *et al.* (2014). Además, aunque existen varios trabajos sobre el cambio tecnológico y su posible efecto sesgado sobre la cualificación de la mano de obra en los países desarrollados, este tipo de trabajos son escasos en los países en desarrollo.

En resumen, contribuimos a la literatura relacionada con este campo en varios aspectos. En primer lugar, añadimos el caso inexplorado de Ecuador a la literatura existente sobre este tema para algunos países de América Latina. En segundo lugar, como los trabajos anteriores no han incluido generalmente entre las innovaciones ni las innovaciones organizativas ni las de marketing, ampliamos el enfoque de nuestro estudio al incluir estas categorías de innovación conjuntamente con las innovaciones tecnológicas más tradicionales (de producto y de proceso). En tercer lugar, no solo nos preocupamos por la dimensión de creación de empleo que puede tener la innovación sino también por la calidad de estos trabajos.

Nuestros resultados ponen de relieve que la innovación no solo tiene un efecto en el empleo en la economía, sino que también está vinculada a las dimensiones de mayor calidad de los puestos de trabajo anteriormente mencionada. Obtenemos, en particular, que hay un papel relevante en Ecuador para las innovaciones de producto y de marketing como herramientas para el aumento del empleo en el corto y el medio plazo. Además, la innovación de producto está asociada positivamente con la composición de la cualificación de la mano de obra en las empresas. Finalmente, las empresas innovadoras también muestran salarios promedio más altos por empleado.

Este tipo de estudio es muy relevante para un país en desarrollo como Ecuador, donde no está ampliamente difundido entre las empresas el desempeño de actividades tecnológicas de un modo intensivo. Para los políticos, puede ser interesante saber que las innovaciones de producto y de marketing contribuyen a la creación de empleo, al menos a corto y medio plazo (dado que nuestro horizonte temporal abarca un período de tres años), que las innovaciones de producto también ejercen presión sobre las necesidades de capital humano que tienen las empresas y que la economía debería facilitar esta cuestión, y que ser una empresa innovadora en general está asociado positivamente a la posibilidad de que los trabajadores de esa empresa ganen salarios en promedio más altos. Para un país sin demasiada experiencia en "cultura innovadora", este tipo de estudios contribuye a resaltar, con el apoyo de la evidencia empírica, los beneficios de la innovación y la necesidad de promoverla.

Finalmente, el gobierno ecuatoriano recientemente ha puesto a disposición de los investigadores una segunda ola de la Encuesta Nacional de Actividades de Innovación (NIAS) que se realizó en el año 2015 y que proporciona información de datos a nivel de empresa para el período 2012-2014. Al agrupar la información de ambas olas de la encuesta, disponemos de 9.090 observaciones correspondientes a 8.025 empresas diferentes. De nuevo, las empresas se han extraído de la población en el último Censo Económico Ecuatoriano (2010) y cubren todas las regiones del país, manteniendo la representatividad de los distintos estratos de tamaño de la industria. Se incluyen además todo tipo de sectores siguiendo la clasificación de la CIIU Rev. 4 de las Naciones Unidas, excluyendo agricultura. De nuevo, responder el cuestionario es obligatorio para las empresas.

En el Capítulo 4 de la Tesis, la atención se centra en el uso de las dos olas de NIAS para identificar los efectos sobre las inversiones privadas de las empresas y las decisiones de realizar actividades de I+D que ejerce la existencia y provisión de subsidios. Estamos interesados en el estudio de este tema para un país en desarrollo como Ecuador, donde la experiencia tanto en la provisión de subsidios como en la inversión privada en I+D por parte de las empresas no tiene una larga tradición. Para los países de América Latina, encontramos algunos estudios sobre los efectos del apoyo público. Sin embargo, esta investigación disponible no considera los subsidios y no distingue qué parte del cambio en la inversión de la empresa es financiada privadamente o financiada por el sector público. Ecuador ha estado tratando de intensificar sus políticas de innovación para resolver las deficiencias detectadas en la cantidad de inversión privada de las empresas, pero aún no hay evidencia sobre la efectividad del esfuerzo público realizado.

Resumen

En este capítulo, exploramos el gasto innovador de las empresas en Ecuador y su relación con el apoyo público a través de la provisión de subsidios públicos. Uno de los objetivos de este estudio no es solo verificar si las subvenciones aumentan la inversión o el esfuerzo *total* de la empresa en I+D e inversiones de innovación relacionadas (margen intensivo), sino también averiguar si el efecto del apoyo público evidencia la presencia de "desplazamiento" (*crowding out*) de la inversión privada. Además, como segundo objetivo se tiene contribuir al aumento del debate sobre la eficacia de los fondos públicos de innovación en los países en desarrollo, ya que la mayoría de los estudios se centran en los países desarrollados. En los países en desarrollo, donde la disponibilidad de fondos es muchas veces restringida, este tipo de estudios es relevante para que los legisladores diseñen mejores instrumentos para apoyar la innovación. Finalmente, también estamos interesados en obtener niveles umbrales para el apoyo público que induzcan a las empresas a realizar actividades de I+D (margen extensivo de los efectos de los subsidios). Para todos estos propósitos, seguimos el marco analítico en los trabajos de González *et al.* (2005) y Arqué-Castells y Mohnen (2015), marco que nos sirve para ilustrar cómo los subsidios públicos afectan a las decisiones óptimas de I+D de las empresas. En su modelo, las empresas reaccionan ante los subsidios esperados cuando toman decisiones óptimas sobre la realización de actividades de I+D y el esfuerzo en la inversión. Los métodos de estimación considerados se ocupan de cuestiones de simultaneidad en lo que respecta a los subsidios y a las decisiones de inversión en I+D, y también de los potenciales problemas de selección de muestra. La preocupación por temas econométricos de endogeneidad por selección de muestra tiene que ver con la selección no aleatoria de las empresas en el grupo de solicitantes exitosos de un subsidio y la probable selección no aleatoria de las mismas en la realización de actividades de I+D.

Nuestros resultados obtenidos en este Capítulo de la Tesis son múltiples. En primer lugar, los solicitantes exitosos de subsidios parecen ser empresas con probables limitaciones financieras para invertir en proyectos de I+D. Además, parece que hay una preferencia de los organismos públicos por financiar empresas con cierta sofisticación tecnológica y mayores riesgos procedentes de los mercados de exportación. Sin embargo, las agencias públicas probablemente no solo seleccionan empresas que enfrentan fallos del mercado, sino que también seleccionan empresas con mayor tradición y volumen en términos de ventas, poder de mercado y buenas expectativas de negocio. En segundo lugar, obtenemos que cuanto mayor es el subsidio esperado para una empresa, más probable es que realice actividades de I+D y que mayor sea su esfuerzo óptimo de inversión. Por lo tanto, los subsidios públicos a las empresas para la I+D en Ecuador aumentan el esfuerzo *total* de la empresa en su inversión en I+D. Sin embargo, los resultados también indican la presencia de un efecto de "desplazamiento" (*crowding out*) parcial de la financiación pública en lo que respecta a la inversión privada. Esto significa que el esfuerzo privado es menor con el subsidio de lo que hubiera sido sin el subsidio. En tercer lugar, con un subsidio no superior al 10%, se inducirá la inversión en estas actividades del 91% de las empresas que no realizan I+D. Finalmente, la retirada de subsidios solo afectaría a un porcentaje muy pequeño de empresas que abandonarían el ejercicio de actividades de I+D (el 0,1%). Esto indica que el financiamiento público se está dirigiendo en gran medida a las empresas que habrían realizado I+D incluso si no hubiera un subsidio.

Dado que Ecuador no tiene todavía una fuerte tradición en la realización de actividades de innovación por parte de las empresas, en general se juzga como positivo que el financiamiento público sea capaz de aumentar el esfuerzo *total* de I+D de la empresa. Pero probablemente tanto las agencias públicas del país que proporcionan subsidios como las empresas del país que los reciben, necesitan un período más largo para explotar el proceso de "aprender haciendo" asociado a la provisión de apoyo público. El efecto de "desplazamiento" (*crowding out*) que se encuentra en los datos podría indicar que las agencias públicas deberían ser más claras en sus requisitos para orientar mejor sobre el uso de estos recursos. De lo contrario, algunas empresas podrían tener incentivos para desviar el dinero hacia otro tipo de inversiones dentro de la empresa, principalmente aquellas empresas que sufren algunas limitaciones financieras. También puede indicar un desajuste entre las ganancias esperadas de las empresas fruto de las actividades innovadoras y lo que realmente obtienen de la innovación. Si las expectativas eran mejores que la realidad, pueden adaptar sus gastos de I+D sin arriesgar tanto su propio dinero y sustituirlo parcialmente por los fondos públicos.

En lo que sigue a continuación en esta Tesis Doctoral, se incluyen los siguientes capítulos. El Capítulo 2 tiene como título: "Uso de las TICs, inversiones en I+D y en capacitación de los trabajadores, productividad de las empresas y márgenes de beneficio empresarial: el caso del sector manufacturero ecuatoriano". El Capítulo 3 se titula: "Innovación y crecimiento del empleo en las empresas ecuatorianas". El Capítulo 4 lleva por título: "Grado de eficacia del apoyo público sobre el esfuerzo inversor en innovaciones de las empresas ecuatorianas". Por último, el Capítulo 5 de esta Tesis Doctoral presenta las conclusiones generales de cada uno de los Capítulos de la Tesis.

Chapter 1: Introduction

The Ecuadorian economy is still heavily dependent on oil prices and agriculture. The primary sector exports account for more than 80% of total exports (United Nations, 2013). The Ecuadorian government is very much interested in transforming the economy into a more knowledge oriented one. However, little is known for this country about the effects of innovation activities on firms' performance in order to properly improve public policies. Since 2013, Ecuador has been trying to improve its productive structure. Objective 10 of the National Development Plan SENPLADES (2013) explained the problems of the industrial sector in Ecuador, especially for manufacturing. The Ecuadorian manufacturing exports were on average 8.9% of total exports (World Bank, 2013) and, from them, high technology exports represented, on average, 5.5% (United Nations, 2013). On the other hand, manufacturing imports represented, on average, 74.79% of total imports. The global unbalance between manufacturing exports and imports was even more problematic for the economy since the year 2000, when Ecuador adopted American dollars (USD) as its local currency and lost its monetary policy. As regards innovation, the situation of the economy was not better. For instance, in 2008 the R&D investment ratio over GDP was 0.25% (UNESCO-Institute for Statistics, 2011). Therefore, combining the situation of exports and innovation, the purpose of the Ecuadorian government with Objective 10 of the National Development Plan SENPLADES (2013) was the establishment of public policies to modify productive structures and promote industry competitiveness through innovation activities.

With these purposes, the first step taken by the Ecuadorian government was to characterize the Ecuadorian productive structure by gathering microeconomic information about firms in the country through the elaboration of a National Economic Census in 2010, covering the entire population of Ecuadorian firms. The Census was conducted by the Ecuadorian Statistics and Census Office (INEC). This is the last Ecuador Economic Census available and it includes 511,130 firms from all productive sectors in the economy. It includes information on firms' characteristics like, for instance: age, location, legal status, industrial sector, employment, sales and main clients, costs, revenues and fixed assets, and some innovation activities such as R&D and workers training investments and ICT use.

Chapter 2 in this Thesis uses precisely the universe of manufacturing firms in the Ecuador Economic Census (2010) to study the relationship between firms' innovation activities and firms' productivity and markups. A key driver of productivity is supposed to be innovation. Moreover, both innovation and productivity may affect the firms' capacity to set prices above marginal costs. As innovative activities, we consider R&D and workers training investments and ICT use. Whether these investments are important for productivity and the capacity to set higher markups in developing countries are interesting development policy questions. Nevertheless, using the last Economic Census of Ecuador for manufacturing firms, 88.34% of them are not involved in any of the three considered innovation activities. All this highlights that Ecuadorian manufacturing firms have not yet obtained all the benefits from innovation activities. The scarce utilization of this database for an empirical analysis not merely descriptive, makes this work novel and pioneer for Ecuador.

In this sense, understanding that knowledge creation is multidimensional, our objectives in this Chapter are manifold. First, we are interested in explaining the joint likelihood of firms carrying out R&D, workers training and use of ICT. The joint likelihood of these activities will require the estimation of a trivariate *probit* model taking into account the potential interrelation among them. Second, we are also interested in explaining firms' determinants of R&D and workers training investment intensities. Unfortunately, the database does not have information about ICT expenditures. Selectivity issues are taken into account by estimating bivariate *Heckman* sample selection models. Third, we introduce estimates from previous stages in a Crépon-Duguet-Mairesse (CDM, 1998) framework to study the linkages between innovation activities and firms' productivity. We do this by employing alternative measures of productivity such as labour productivity and Total Factor Productivity (TFP hereafter) estimates from *Cobb-Douglas* and *Translog* production functions. Finally, we check whether innovation activities not only affect firms' productivity but also have an influence in the firms' capacity to set prices above marginal costs and, hence, markups. Estimated firms' markups follow from the production function estimation. The implementation of a CDM approach allows the incorporation of control function corrections (see Wooldridge, 2010) for testing and handling the possibility of endogeneity of innovation variables in the productivity and markups equations.

The novelties in this Chapter are as follows. First, we use a broad definition of firms' innovation activities that includes investments in R&D and workers training as well as ICT usage. This is expected to contribute to the minimization of omitted variables bias when trying to understand the consequences for firms' performance of adoption and intensity of such investments. Second, we go one step further in the CDM framework by incorporating a second firms' performance measure, besides the typical one of productivity, that is, firms' markups. Therefore, we are not only going to answer the question about the drivers of innovation adoption and innovation investments and, later, their effects on firms' TFP, but also breaking new ground in investigating the role of innovation activities and TFP on firms' markups formation. Third, in this final stage of our estimation procedure in the Chapter, we can distinguish, by conditioning to TFP in the markups regression, whether the effect of innovation variables on markups operates through efficiency, that is marginal costs proxy by TFP, and/or through the higher capacity of firms to set prices above marginal costs, since innovation likely fosters higher quality products. Finally, literature integrating all these elements in a unified framework is scarce and mostly concerned with developed economies. Hence, to find out whether these types of activities have also a relevant role for developing countries is of considerable interest not only for managers but also for policy makers, since whether this type of investments are important sources of productivity and capacity to fix higher markups in developing countries are interesting development policy questions. Furthermore, this is the first study of this type for Ecuador.

The main results in the Chapter can be summarised as follows. First, the professionalization and good business practice variables such as belonging to a business group, having access to finance, performing activities of market research, accountancy, and having environmental concerns, explain higher propensities and intensities of R&D and workers training investments, and ICT use. Second, the three innovation activities affect positively firms' TFP and markups. Third, part of the effect of innovation activities on markups operates through influencing prices, and not only efficiency. Fourth, we detect some demand driven innovations and markups. Fifth, we also detect some evidence about learning and product quality requirements from international markets encouraging both innovations and higher markups. Finally, we obtain results that may be indicative of financial constraints affecting innovation, softened for firms belonging to a business group or with access to external finance.

This clearly evidences the important role for public policy in encouraging the spread of these activities among firms in order to obtain sound effects on firms' performance measures such as productivity and markups. There is also room for government intervention in alleviating Ecuadorian manufacturing firms' financial constraints affecting these investments.

The second step the Ecuadorian government took in the direction of collecting relevant data in order to diagnose the productive structure and the state of innovation in Ecuadorian firms, is carrying out the Ecuadorian National Innovation Activities Survey 2013 (NIAS). This is a survey sponsored by the Ecuadorian National Statistics and Census Office (INEC) and the Secretary of Superior Education, Science, Technology and Innovation (SENESCYT). It was the first time that Ecuador was making a survey about innovation decisions and performance at the firm level. The information in the survey corresponds to a three years' period (2009-2011) and it is quite similar in structure and variables to the Community Innovation Surveys (CIS) for European countries. The survey covers 2,815 firms extracted from the population in the last Ecuadorian Economic Census (2010), covers all regions in the country and is representative of industry-size strata. In the survey, NIAS includes all type of sectors following the ISIC Rev. 4 classification from the United Nations, except agriculture. Answering the questionnaire is compulsory for firms.

In Chapter 3 of the Thesis, the main source of information is NIAS. The main objective here is the study of the effects of innovation on firms' employment growth. We consider four types of innovations: product, process, organizational and marketing innovations. We apply the methodology developed by Harrison *et al.* (2014) extended to include also marketing and organizational innovations. In addition to the core objective of the Chapter, we also have some supplementary goals. In this sense, we are interested in providing some evidence about the link between different types of innovations and the composition of the firm's labour force in terms of skills and wages. We can consider both higher skills and wages as indicators of higher quality labour being required and created by more innovative firms. If this was the case, not only innovation is socially and economically desirable because it generates employment growth but also because it might help improving jobs quality by affecting skill composition of labour and wages (technology based wage *premia*). For instance, product innovation may increase variety and quality and, hence, may lead to skill upgrading and to higher wages. While Ecuador does not have a high unemployment rate (5.23% during the analysed period), however, it has a high percentage of vulnerable employment (42.73% of total employment). Employment vulnerability is an indicator to measure the quality of jobs that was emphasized by the United Nations Millennium Goals for 2015.

Most of the evidence about the effects of innovation on employment are from developed countries and, furthermore, only about the two types of innovations considered in editions of the Oslo Manual previous to the one of 2005 (that is product and process innovations). However, it is interesting to notice that our work is the first one that considers marketing as a different innovation type to be considered separately in the context of the Harrison *et al.* (2014) model. Again, although there are several studies about technological change and skill bias in developed countries, they are scarce in developing countries.

In summary, we contribute to the related literature is several aspects. First, we add the unexplored case of Ecuador to the existent literature on this topic for some Latin American countries. Second, as previous works have not generally included among innovations either organizational and/or marketing innovations, we enlarge the focus of our study by including these categories of innovation jointly with the more traditional technological innovations (product and process). Third, we are not only focused on the jobs creation dimension of innovation but also in the quality of these jobs.

Our results highlight that innovation not only has an employment effect in the economy but it is also linked to the before mentioned higher quality dimensions of jobs. We obtain, in particular, a relevant role in Ecuador for product and marketing innovations as tools to increase employment in the short and medium run. Additionally, product innovation is positively associated with firms' skills composition. Finally, innovative firms display higher average wages *per* employee.

This type of study is highly relevant for a developing country like Ecuador, where it is not widely spread among firms the performance of technological activities in a highly intensive way. For politicians it might be interesting to know that both product and marketing innovations contribute to employment creation at least in the short and medium run (since our temporal horizon covers a period of three years), that product innovations also put pressure on higher skills on human capital that should be available for the economy, and that being innovative in general is positively associated to the possibility of workers earning higher average wages. For a country with not too much experience in "innovative culture" this type of studies contributes to highlight, with the support of empirical evidence, the benefits from innovation and the need to promote it.

Finally, the Ecuadorian government has recently made available for researchers a second non-overlapping wave of the National Innovation Activities Survey (NIAS) that was performed in the year 2015 and that provides firm-level data information for the period 2012-2014. Pooling information from both waves of the survey, there are 9,090 observations corresponding to 8,025 different firms. Again, firms have been extracted from the population in the last Ecuadorian Economic Census (2010).

In Chapter 4 of the Thesis, the focus is on the use of the two waves of the NIAS for identifying the effects over firms' private investment and decisions to perform R&D of the existence of subsidies. We are interested in a developing country like Ecuador where experience both in the provision of subsidies and private investment in R&D by firms has not a long tradition. For Latin American countries, we found a few studies about the effects of public support. However, this research does not consider subsidies and does not distinguish which part of the change in the firm's investment is privately funded and/or funded by the public sector. Ecuador has been trying to intensify its innovation policies to solve deficiencies in the amount of firms' private investment, but there is not yet evidence about effectiveness of the public effort.

In this Chapter, we explore firms' innovative expenditure in Ecuador and its relationship with public support through public subsidies. One of the aims of this study is not only checking whether subsidies increase the total firm's investment or effort in R&D and related innovation investments (intensive margin), but also finding out whether the effect of public support evidences the presence of *crowding out* or *crowding in* on private investment. Additionally, a second aim is contributing to the increase of debate about innovation public funds effectiveness in developing countries, since most of studies are focussed on developed countries. In developing countries, where the availability of funds is many times restricted, this type of studies is relevant for policy makers to design better instruments to support innovation. Finally, we are also interested in getting threshold levels to public support that induce firms to perform R&D activities (extensive margin effects of subsidies). For all these purposes, we rely on González *et al.* (2005) and Arqué-Castells and Mohnen (2015) analytical framework to illustrate how public subsidies affect optimal R&D decisions. In their model, firms react to expected subsidies when taking optimal decisions about performance of R&D and effort in the investment. The estimation methods deal with both simultaneity issues as regards subsidies and R&D investment decisions and also selection concerns. Selectivity concerns have to do with non-random selection for firms in the group of successful applicants and likely non-random selection into the performance of R&D activities.

Our results are manifold. First, subsidy successful applicants seem to be firms with likely financial constraints to invest in R&D projects. Also, there seems to be a preference from public agencies to finance firms with certain technological sophistication and higher risk from export markets. However, public agencies are probably not only picking firms facing market failures, but also cherry picking quite established firms in terms of sales, market power and good business expectations. Second, we obtain that the higher the expected subsidy for a firm the more likely it is to perform R&D and the higher the optimal investment effort. Hence, firms' public subsidies to R&D in Ecuador increase the *total* firm's effort in R&D investment. However, results also indicate the presence of a partial *crowding out* effect of public funding as regards private investment. This means that private effort is smaller with the subsidy than it would have been without the subsidy. Third, with a subsidy no higher than 10%, about 91% of non-R&D performing firms will be induced to invest. Finally, subsidy withdrawal only affects a very little percentage of firms that would abandon performance of R&D (0.1%). This indicates that public funding is being directed to a high extent to firms that would have performed R&D even if there was not a subsidy.

Since Ecuador has not a strong tradition in firms' innovation activities, it is generally good that public funding increases the *total* firm's R&D effort. But probably both the country public agency and the firms in the country need a longer period to exploit the process of "learning by doing" associated to the provision of public support. The *crowding out* effect found in the data could be signalling that may be public agencies should be clearer in their requirements for the use of these resources, otherwise some firms might have incentives to deviate the money towards other firms' investments, mainly firms that suffer from some financial constraints. There can also indicate a mismatch between firms' expected profits from innovative activities and what they really get from innovation. If expectations were better than reality, they can adapt their R&D expenditure by not risking so much their own money and substituting it partially by the public funds.

In what follows, hence, this Thesis dissertation is divided in the following Chapters. Chapter 2 under the title "ICT use, investments in R&D and workers training, firms' productivity and markups: The case of Ecuadorian manufacturing". Chapter 3 entitled "Innovation and employment growth in Ecuadorian firms". Chapter 4 titled "Public support effectiveness on innovation effort in Ecuadorian firms". Finally, Chapter 5 presents the general conclusions from each one of the Thesis Chapters.

Chapter 2 Ict use, investments in R&D and workers training, firms' productivity and markups: The case of Ecuadorian manufacturing

2.1 Introduction

Since 2013, Ecuador has been trying to improve its production structure. Objective 10 of the National Development Plan SENPLADES (2013) explains the problems of the manufacturing industry in Ecuador. The manufacturing sector growth during 2002-2006 was on average 2.9% and its contribution to GDP was never above 15.2% in the last ten years (Banco Central del Ecuador, 2014). The primary sector exports account for more than 80% of total exports (United Nations, 2013). The Ecuadorian manufacturing exports are on average 8.9% of total exports (World Bank, 2013) and, from them, high technology exports represent, on average, during the same period, 5.5% (United Nations, 2013). On the other hand, manufacturing imports represent, on average, 74.79% of total imports during 2005-2012. The global unbalance between manufacturing exports and imports is even more problematic for the economy since the year 2000, when Ecuador adopted American dollars (USD) as its local currency and lost its monetary policy. As regards innovation, the situation of the economy is not better. For instance, in 2008 the R&D investment ratio over GDP was 0.25% (UNESCO-Institute for Statistics, 2011). Therefore, combining the situation of exports and innovation, the purpose of the Ecuadorian government with Objective 10 of the National Development Plan SENPLADES (2013) is the establishment of public policies to modify production structures and promote manufacturing competitiveness through innovation activities. The Ecuadorian government is very much interested in the analysis of the effects of innovation activities on firms' performance in order to properly improve public policies. However, little is known. That is why one of the purposes in this chapter is to provide some light about the relationship between the performance of innovation activities and manufacturing firms' productivity, an essential factor for firms' competitiveness.

There exists abundant literature about economic growth and factors that originate it. Already Solow (1957) highlighted that one of the fundamental factors which explains countries' economic growth is related with technological changes introduced by firms, and that increase firms' productivity. Later, Aghion and Howitt (1992, 1998) would develop models confirming this idea by incorporating innovation activities as drivers of technological change, complementing, therefore, the prelaminar ideas by Schumpeter (1942) about *creative destruction*.

While is true that, traditionally, most of the studies about innovation and productivity have focused on R&D investments as one of the most important aspects of innovation, nowadays are considered into account other dimensions of the firms' innovative process. We mean activities such as workers training investments and ICT use by firms that contribute to firms' internal knowledge and technological change.

In this context, the purpose of this chapter is to shed more light on the relationship between firms' innovation activities and their economic performance in two dimensions, productivity and markups. Recent works for developed countries highlight that innovation activities not only may affect productivity but also the capacity of firms to set prices above marginal costs. We extend this type of analysis to a developing country such as Ecuador. We use in this chapter the Economic Census of Ecuador (INEC, 2010) for manufacturing firms. This census information is referred to the year 2009. We will exploit information about firms' R&D and workers training investments and use of ICT, as well as about general firms' characteristics. The scarce utilization of this database for an empirical analysis not merely descriptive, makes this work novel and pioneer for Ecuador. In this sense, our objectives in this chapter are manifold. First, we are interested in explaining the joint likelihood of firms carrying out R&D, workers training and use of ICT. The joint likelihood of these activities will require the estimation of a trivariate *probit* model taking into account the potential interrelation among them. Second, we are also interested in explaining firms' determinants of R&D and workers training investment intensities. Unfortunately, the database does not have information about ICT expenditures. Selectivity issues are taken into account by estimating bivariate *Heckman* sample selection models. Third, we introduce estimates from previous stages in a Crépon-Duguet-Mairesse (CDM, 1998) framework to study the linkages between innovation activities and firms' productivity. We do this by employing alternative measures of productivity such as labour productivity and productivity estimates from *Cobb-Douglas* and *Translog* production functions. We are interested in checking the robustness of our results since estimation of Total Factor Productivity (TFP hereafter) is restricted by the cross-section nature of the database. Finally, we check whether innovation activities not only affect firms' productivity but also have an influence in the firms' capacity to set markups.

The novelties in this chapter are as follows. First, we use a broad definition of firms' innovation activities that includes investments in R&D and workers training as well as ICT usage. This is expected to contribute to the minimization of omitted variables bias when trying to understand the consequences for firms' performance of adoption and intensity of such investments. Second, we go one step further in the CDM framework by incorporating a second firms' performance measure, besides the typical one of productivity, that is, firms' markups. Therefore, we are not only going to answer the question about the drivers of innovation adoption and innovation investments and, later, their effects on firms' TFP, but also breaking new ground in investigating the role of innovation activities and TFP on firms' markups formation. Third, in this final stage of our estimation procedure in the chapter, we can distinguish, by conditioning to TFP in the markups regression, whether the effect of innovation variables on markups operates through efficiency, that is marginal costs proxy by TFP, and/or through the higher capacity of firms to set prices above marginal costs, since innovation likely fosters higher quality products. Finally, literature integrating all these elements in a unified framework is scarce and mostly concerned with developed economies. Hence, to find out whether these types of activities have also a relevant role for developing countries is of considerable interest not only for managers but also for policy makers, since whether this type of investments are important sources of productivity and capacity to fix higher markups in developing countries are interesting development policy questions. Furthermore, we are not aware of any study of these characteristics and aims for Ecuador.

The main results in the chapter can be summarized as follows. First, the professionalization and good business practice variables such as belonging to a business group, having access to finance, performing activities of market research, accountancy, and having environmental concerns, explain higher propensities and intensities of R&D and workers training investments, and ICT use. Second, the three innovation activities affect positively firms' TFP and markups. Third, part of the effect of innovation activities on markups operates through influencing prices, and not only efficiency. Fourth, we detect some demand driven innovations and markups. Fifth, we also detect some evidence about learning and product quality requirements from international markets encouraging both innovations and higher markups. Finally, we obtain results that may be indicative of financial constraints affecting innovation, softened for firms belonging to a business group or with access to external finance.

Since 88.34% of manufacturing firms in Ecuador are not involved in any of the three considered innovation activities, this clearly evidences the important role for public policy in encouraging the spread of these activities among firms in order to obtain sound effects on firms' performance measures such as productivity and markups. There is also room for government intervention in alleviating Ecuadorian manufacturing firms' financial constraints affecting these investments.

The chapter is organized in the following sections. Section 2.2 provides an overview of related literature. Section 2.3 introduces the dataset and performs a descriptive study of some relevant variables in the analysis. Section 2.4 is devoted to methodological concerns and procedures at each stage of estimation and presents obtained results. Hence, Section 2.4.1 is focused on the joint estimation of the R&D, workers training and ICT use binary choice firms' decisions by using a trivariate *probit*; Section 2.4.2 on the estimation of the R&D and workers training investment intensity equations (correcting for potential selectivity bias using a bivariate *Heckman* estimation method); Section 2.4.3 examines the relationship between productivity and the three innovation activities considered; and, finally, Section 2.4.4 focus on the relationship of these activities with firms' markups. Estimated firms' markups follow from the production function estimation. Previous steps in estimation allow for endogeneity corrections of innovation variables both in the productivity and markups equations. Section 2.5 concludes.

2.2 Literature review

Among the empirical studies analysing the relationship between R&D activities and productivity we find the works by Griliches (1970, 1979), Máñez *et al.* (2015), Añón *et al.* (2011), and Doraszelski and Jaumandreu (2013), among others. In them, it is generally found that there exists a positive and statistically significant relationship between firms' productivity and R&D performance. Some relevant arguments that justify this finding are the following (Hall, 2011): on the one side, firms investing in R&D may both increase its productive efficiency and also obtain better products, increasing demand and reducing production costs. On the other hand, firms investing in R&D likely face more favourable growth perspectives, which contributes to a better exploitation of economies of scale in production, with the associated costs reduction.

In the line of research focused on the relationship between productivity, innovation and R&D investment, we find the seminal work by Crépon *et al.* (1998) that, using cross-sectional data for French manufacturing firms, develops the so-called CDM model, which explains the before mentioned relationships through sequential estimation steps. In the first step, the R&D decision and investment equations are estimated. In the second step, the R&D estimates from the previous step are used as regressors for estimation of a firm's innovation outcomes equation. Finally, the estimated innovation outcomes from the second step enter as explanatory variables in a labour productivity equation. The idea behind the CDM is that R&D expenses generate knowledge for firms, and this knowledge can be measured by innovation outcomes (patents, new processes, new products, *inter alia*) that can generate a subsequent positive effect in the firms' productivity. Following this approach, Crespi and Zúñiga (2012) use the CDM model and find in six Latin American countries (Argentina, Chile, Colombia, Costa Rica, Panama, and Uruguay) that firms' improvements in new technologies enhance its productivity. However, Benavente (2006) finds no impact of innovation (R&D) on productivity for Chilean firms. Likewise, Hall (2011) does a review of studies using CDM methods that covers data from Germany, Spain, United Kingdom, Italy, Sweden, China, Finland, Norway, Estonia and The Netherlands. She concludes that there is not always found a positive and significant relationship between productivity and innovation, and that this especially happens for process innovation.

However, there is not a unique path to apply the CDM model approach. It depends on the researchers' available information in a particular database, the nature of this information, as well as on researchers' interests. Thus, there are papers applying the CDM sequence going directly from innovation inputs to productivity (in case of absence of innovation outputs in the databases), and/or papers that consider a wider definition of innovation activities by including not only R&D performance but also other technological and knowledge related activities in the firm such as workers training and information and communication technology (ICT hereafter) use, or some of these latter activities in isolation instead of considering R&D.

There is no doubt about human capital being an important driver of economic growth. Hence, the expected role for workers training on firms' productivity has its roots on the maintenance and improvement of human capital of workers. For Belgian firms, Konings and Vanormelingen (2015, p. 485) find, for instance, "that an increase in the share of trained workers by 10 percentage points is associated with 1.7% to 3.2% higher productivity". For German establishments, Zwick (2006) shows that increasing training intensity has a positive and significant effect on productivity. A similar result is obtained by Colombo and Stanca (2014) for Italian firms. Another example that combines into one variable expenditures on R&D and workers training is the work by Aw *et al.* (2007). For firms in the Taiwanese electronics industry, these authors find that investments in R&D/workers training increase productivity returns from exporting, but do not have an independent statistically significant effect.

The OECD (2009, p. 90) definition for ICT is the following: "products intended to fulfil or enable the function of information processing and communications by electronic means, including transmission and display". The arguments for ICT contributing to productivity are diverse. First, adds to firms' internal knowledge through something termed *Internet of things*, which is defined by ITU (2012, p. 1) as "A global infrastructure for the information society, enabling advances services by interconnected (physical and virtual) things based on existing and evolving interoperable information and communication technologies". Hence, enables firms to be better connected, to better manage information and to have access to external knowledge. Second, may affect productivity through more efficient organization of production or the supply of new and/or better products and services. In this respect, Añón-Higón (2012) for UK SMEs, and distinguishing among different types of ICT applications, finds that "ICT operate primarily as efficiency-enhancing technologies, although specific market-oriented applications (that is, website development) exhibit the potential to create competitive advantage through product innovation". In this sense, ICT should not be only understood as a general purpose technology (Bresnahan and Trajtenberg, 1995). Deepening into this idea, it may happen ICT use to be more orientated towards affecting business processes and work practices (e.g. just-in-time inventory management or electronic coordination with suppliers) and, hence, enabling cost reductions, or towards new services (or improved service speed), new ways of doing business, new ways of marketing (e.g. e-commerce) and greater customization.

Among the empirical studies that find evidence of positive effects of ICT on productivity with firm-level data, we have van Leeuwen and van der Wiel (2003) for

The Netherlands, Brynjolfsson and Hitt (2003) and Rincón *et al.* (2013) for the US, and Castiglione (2012) for Italy. Furthermore, from the ones that also consider R&D, van Reenen *et al.* (2010) find strong effects of R&D on productivity but little evidence for ICT. However, studies of the impacts of ICT on productivity are scarce in developing countries. Two recent exceptions are found in Commander *et al.* (2011) and Aboal and Tacsir (2015), where for Brazilian and Indian, and Uruguayan firms, respectively, it is obtained that investments in ICT are positively associated with productivity. There is also a previous study for Chinese firms that finds that ICT contributes significantly to productivity (Motohashi, 2008).

It is relevant to control simultaneously for the three technological investments (R&D, workers training –human capital, and ICT), both in the productivity and markups equations, in order to avoid omitted variable bias (provided the potential relation among them). It is not surprising that very likely R&D-based knowledge and knowledge based on human capital (through workers training) and ICT interact with each other. However, studies at the firm-level jointly controlling for the three knowledge factors are scarce. Instead, we mainly find works focussed on one of them or, alternatively, on two of them. See, for instance, the works by Greenan *et al.* (2001), Polder *et al.* (2010) and Hall *et al.* (2013), for French, Dutch and Italian firms, respectively, which look at R&D and ICT; or the works by Black and Lynch (2001) and Bresnahan *et al.* (2002) for US firms that consider ICT and human capital.

2.3 Data and descriptive analysis

In this chapter we use the Economic Census of Ecuador 2010. It is a census including 511,130 firms. The information corresponds to the year 2009. It includes firms' characteristics like, for instance: age, location, legal status, industrial sector, employment, sales and main clients, costs, revenues and fixed assets that, among others, will be used in the empirical analysis.

For this study, as we are focused on the manufacturing sector, the number of firms gets reduced to 44,109.[1] However, after cleansing the data of firms with missing information for the relevant variables in this study, we end up with a sample of 42,292 firms. We group firms into 12 sectors (see Appendix C2. 1).

The first step of our descriptive analysis is focused on firms' participation rates in innovation activities. Since the survey includes explicit and particular questions about R&D, workers training and ICT adoption, we find that 412 firms (0.97%) perform R&D, 1,828 (4.32%) invest in workers training and 4,173 (9.87%) use ICT. This clearly evidences that this type of activities is not widely spread among manufacturing firms in Ecuador (88.34% of firms are not involved in any of them). Moreover, conditioning to the group of firms that at least performs one of these activities, the highest percentage corresponds to firms performing only one of them (74.58%) and the lowest to firms performing the three (4.46%). Firms performing two activities represent 20.96%.

Next, we provide some descriptive results to characterize, through some basic firm characteristics, groups of firms by type of innovation strategy. For this purpose, we perform a simple regression analysis and estimate the following equation:

$$(1) \qquad \ln y_i = \alpha + \beta_1 RD_i + \beta_2 WT_i + \beta_3 ICT_i + X_i^{'}\gamma_i + v_i$$

[1] Apart from the manufacturing sector, the Economic Census of Ecuador 2010 also includes services, which account for 87.12% of firms (only wholesale and retail represent 59.9% of firms from total services), and agriculture, extraction of natural resources, construction, and water supplies and gas, which account for less than 1% of firms each.

where the dependent variable, y_i, is alternatively firm sales per worker, capital per worker, materials per worker and size (as measured by the number of employees). The variables RD_i, WT_i, and ICT_i, are dummy variables capturing firms' performance of R&D, workers training and ICT activities. We also control for employment (except for the size regression), age, and industry dummies.

From the results in Table C2. 1, we observe that firms investing in R&D, workers training and/or ICT are larger, more labour and materials intensive and also with higher labour productivity than firms not doing so. Furthermore, the highest correlation with all these firms' characteristics is found for ICT use and the lowest for R&D performance, being in between the correlation with workers training activities. For each innovation activity considered, estimated coefficients have a semi-elasticity interpretation (notice that dependent variables are in *log* form and innovation variables are dummy variables). Hence, for instance, if we take the estimated coefficients from the labour productivity regression, we obtain that a firm investing in R&D *versus* one not investing has 17.3% higher labour productivity. Also, firms investing in workers training have 37.3% higher labour productivity than firms that do not. Finally, ICT users have 82.5% higher labour productivity than non-users. Although this is just a descriptive analysis from where we cannot yet infer causality, it presents first evidence about firms performing these innovation activities to be different than the ones not performing them in terms of relevant characteristics, including size and labour productivity, among others.

Table C2. 1 Regressions of some firms' characteristics on innovation dummies

	Log(sales/worker)	Log(capital/worker)	Log(materials/worker)	Log(workers)
R&D	0.173**	0.344***	0.134*	0.510***
	(0.0674)	(0.0812)	(0.0744)	(0.0728)
Workers training	0.373***	0.555***	0.397***	0.686***
	(0.0322)	(0.0376)	(0.0363)	(0.0316)
ICT	0.825***	1.047***	0.801***	1.058***
	(0.0225)	(0.0275)	(0.0262)	(0.0198)
Constant	8.918***	7.278***	8.074***	0.568***
	(0.0130)	(0.0165)	(0.0144)	(0.00750)
Observations	42,292	42,292	42,292	42,292
R-squared	0.161	0.109	0.157	0.318

Notes:
1. Robust standard errors in parenthesis.
2. *** p<0.01, ** p<0.05, * p<0.1.
3. Regressions include as controls the following variables: log workers (not included in the final regression), log age and industry dummies.

2.4 Estimation methodology and results

The estimation methodology used in this chapter consists of several stages. In a first stage, we estimate the probability of the three firms' decisions (R&D, workers training and ICT use) taking into account the interrelation between them by using a trivariate *probit* model. In a second stage, we estimate a bivariate *Heckman* sample selection correction model (Heckman, 1979) to properly estimate jointly an investment in R&D equation and an expenditure equation for workers training (notice that the ICT question in the survey is only about usage). In a third stage, in the spirit of CDM models, we retrieve information from previous stages about predicted expenditures, predicted probabilities and corresponding residuals for R&D and workers training investments and ICT use equations, which are employed in productivity and markup regressions to uncover the effects of these activities on firms' performance measures. Finally, we use the estimated input elasticities from a *Translog* production function to get firms' markups estimates that are also regressed on the same innovation variables employed in the productivity equations.

2.4.1 The firms' innovation decisions: R&D, workers training and ICT use

We estimate a standard trivariate *probit* model for the three discrete choices involved in the first stage of our analysis. Let $y^{*}_{1i,j}$ denote a latent variable underlying firm *i's* (*i=1,…,N*) propensity to invest in activity *j* (*j*=R&D, WT or ICT) given firm and structural characteristics x_{1i}. Formally

(2) $y^{*}_{1i,j} = \beta^{'}_{1,j} x_{1i} + \varepsilon_{1i,j}$,

where $\beta^{'}_{1,j}$ captures the effects of explanatory variables on the propensity to perform innovation activity *j* and $\varepsilon_{1i,j}$ denotes idiosyncratic errors that affect $y^{*}_{1i,j}$. The observed dependent variables, $y_{1i,j}$, corresponding to $y^{*}_{1i,j}$ are defined as

(3) $y_{1i,j} = \mathbf{1}\left[y^{*}_{1i,j} > 0 \right]$,

where $\mathbf{1}[\ ]$ denotes the indicator function taking the value one if the condition between squared brackets is satisfied, and zero otherwise. We assume that the three error terms $\varepsilon_{1i,j}$ involved follow a trivariate normal distribution. This specification allows correlations among the three choices to be non-zero. This takes into account that firms' choices may possibly be interrelated. If these correlations are not considered, biased and inconsistent parameter estimates are possible due to the relationships between different types of innovation activities (Greene, 2003). Then, the three-equation system is estimated by simulated maximum likelihood using the GHK simulator for evaluation of the *3*-dimensional integrals.[2] Estimation is performed with the Stata command *cmp*

[2] Multivariate standard normal probability distribution functions are replaced by their simulated counterparts (see Hajivassiliou and Ruud, 1994, and Gourieroux and Monfort, 1996).

developed by Roodman (2011) for estimating fully observed recursive mixed-process models. The program allows implementing a pseudo-simulated maximum likelihood estimator (PSML) that adjusts the estimates of the parameter covariance matrix to take into account heteroscedasticity-robust standard errors (see Huber, 1967 and White, 1982).

The explanatory variables considered are the same for the three choices (they are defined in Appendix C2. 2), although their impact may differ. First, there are three groups of explanatory variables that characterize firms from the point of view of location, industry and legal form. Location is introduced as dummy variables for each province in the country. With its inclusion we try to capture factors related to the provinces that may determine higher or lower propensities to invest in R&D, in workers training or in ICT use. There are 24 provinces in the country, three of which (Pichincha, Guayas and Azuay) account for 53.7% of manufacturing firms.[3] As regards industry dummies (see Appendix C2. 1), they control for industry effects. In the database, there are 9 legal forms applying to manufacturing (see Appendix C2. 2).

Furthermore, we include a group of variables intended to capture the degree of professionalism and modernization of the firm in terms of quality and diligence in management and business practices. Here, we consider whether the firm belongs to an enterprise network or business group, performs activities of market research, performs accounting, has access to external finance, and/or if the company carries out activities for environmental improvement.

[3] There is also a "province" category named "unfenced areas" for territories in conflict.

Additionally, there are other control variables included such as whether the main customer of the firm is foreigner, whether the firm has a craft certification,[4] whether the firms has its own local, whether the surveyed firm is the mother company, and whether it has a male manager. We expect a positive sign for the indicator of the main customer of the firm being foreigner, since competition in international markets is expected to put pressure on firms' innovation activities. It also makes access to information and communication tools more crucial. Thus, for instance, Bratti and Felice (2012) show that there exists a positive relationship between firms' openness to trade and firms' innovation activities. But also one may argue that innovative firms are more likely to enter foreign markets. However, we do not consider here this possibility. The reason has to do with data limitations in the survey as regards the lack of a proper question about firms being or not exporters. The questionnaire is not particularly asking this question but whether the main client of the firm is or is not foreigner. Hence, it would be a very much incomplete proxy for firms' exporting statuses since answering *no* to this question does not guarantee being a non-exporting firm. Some evidence of this is the small number of firms that would be considered exporters in the Ecuadorian manufacturing sector, 236 out of 42,292 firms (0.56%).

Finally, there are two more controls considered: on the one hand, firm age (in logs and its square), which may both capture experience but also questions related to the product life cycle and, on the other hand, firm size (as measured by number of workers

[4] The Craftsman Defense Act (1998) in Ecuador allows people involved in these activities to enjoy some tax benefits. It is meant for natural persons (similar to the self-employed workers in other countries) that may obtain this certification and that likely run small firms in terms of capital and number of employees.

in logs and its square). We expect larger firms to be more likely involved in innovation related activities (Schumpeter, 1942).[5]

The estimated mean marginal effects for the explanatory variables in the vector x_{1i} in model (2)-(3) corresponding to the three firm's choices (R&D, workers training and ICT) are presented in Table C2.2. As regards the group of variables intended to capture the degree of professionalism and modernization of the firm in terms of quality and diligence in management and business practices, results in Table C2.2 indicate that all of them are statistically significant and have a positive sign in explaining the propensities to invest in R&D, workers training and ICT. For the R&D decision, the strongest effect is estimated for the realization of activities of market research, what may indicate that R&D performance is driven in a relevant manner by firm's demand concerns. For the workers training decision, the strongest effects are found for the company carrying out activities for environmental improvement and, again, for market research activities. Finally, for ICT use, the strongest effects are found for firms performing accounting and for firms belonging to an enterprise network or business group, very likely due to the required software and hardware for accounting activities and the more vital necessity of those firms to be interrelated inside the business group. For illustration of the estimated magnitude of marginal effects for these variables, let us take as example the estimated marginal effect for the Enterprise network dummy in the ICT use equation, 0.0982 (see Table C2.2). The interpretation of this value means that should the firm enter a business group, its average estimated probability of ICT use in the data, which is 0.098 (see the heading of column 3 in Table C2.2, would be instead 0.1962 (19.62%).

[5] Descriptive information about all variables involved in the chapter can be found in Appendix C2.3.

Additionally, among the group of control variables included, size has a positive and statistically significant effect in the three choices, but at a decreasing rate (excluding the case of workers training); also age has a positive (but at a decreasing rate) and statistically significant effect, but in this case only for workers training and ICT use; to have a male manager is negatively related with workers training and ICT use; to be the mother company is positively related with workers training and mainly with ICT use; to have a craft certification seems to require investments in workers training but is negatively related with the use of ICT; to have your own local is either non-relevant or it is negatively related with ICT use; and, finally, to have a foreign main customer is not statistically significant to explain the R&D and workers training decisions, but contributes to explain higher likelihood of ICT use.

According to location variables (where the reference category is Pichincha) we obtain that all statistically significant marginal effects are negative, indicating that Pichincha is in general outperforming other Ecuadorian provinces in terms of R&D, workers training and ICT use.[6] Among industries, which reference category is Food, Drinks and Tobacco, the ones that have a higher probability to invest in R&D are Chemicals; Office machinery and electrical equipment; and Communications, precision, optical and medical equipment, all of them classified by the OECD as of medium and

[6] For the R&D decision it has not been possible the estimation of coefficients associated with the following three provinces: Morona Santiago, Galápagos and Santa Elena. Furthermore, the same has happen for the province named Unfenced Areas, in this case affecting not only the R&D decision but also workers training and ICT use. The reason is that, on the one side, for each one of these provinces all firms in the dataset do not invest in R&D and, on the other side, for the province defined as Unfenced Areas, no one firm neither performs workers training and ICT. This provokes in estimation an issue of perfect prediction of zeros for these provinces. However, this is a negligible issue since the number of firms located in all these areas account for only 2.6% of manufacturing firms.

high technology and, thus, more R&D orientated. However, Non-metallic products presents a lower R&D investment probability. For the performance of workers training, also Chemicals, and Communication, precision, optical and medical equipment repeat, but also Rubber and plastic appears on the scene. For ICT use, all industries have higher probability than the reference category, highlighting specially the industries of Rubber and plastic; Wood and paper; Chemicals; Office machinery and electrical equipment; and Communication, precision, optical and medical equipment.

With respect to legal forms, none is statistically significant for the R&D investment decision (the reference category corresponds to the largest group of firms belonging to natural persons). However, for the workers training and ICT use decisions, to be a Private company increases the likelihood of firms performing both activities, although the legal form associated with the higher likelihood of investing in workers training is Association and the one for ICT use is Cooperative.[7]

Correlation coefficients for the error terms associated to the three choices are shown at the bottom of Table C2.2. All of them are positive and statistically significant, giving support to the convenience of estimating a joint maximum likelihood instead of three independent *probit* models.

[7] For the R&D decision it has not been possible the estimation of coefficients associated with the following legal forms: Non-profit company, Foreign company, Local Government company and Credit and saving cooperative. Furthermore, the same has happen for Local Government company and Credit and saving cooperative in the workers training equation and for Foreign company and Credit and saving cooperative in the ICT use equation. It appears again an issue of perfect prediction of zeros in the corresponding firm's choices. However, this is a negligible concern since firms with these legal forms account for only 0.14% of total manufacturing firms.

Table C2. 2 Firms' choices: R&D, Training and IC (Multivariate *Probit*)

		(1) R&D	(2) Training	(3) ICT
	Variables	**y**=Pred. P(R&D=1)=0.010 **dy/dx** (Aver. Marg. Eff.)	**y**=Pred. P(Training=1)=0.043 **dy/dx** (Aver. Marg. Eff.)	**y**=Pred. P(ICT=1)=0.098 **dy/dx** (Aver. Marg. Eff.)
Geographical location	Azuay	-0.000359	-0.00944***	-0.0242***
		(0.00132)	(0.00244)	(0.00303)
	Bolívar	0.00249	-0.0100	-0.0569***
		(0.00506)	(0.00784)	(0.00901)
	Cañar	-0.00369	-0.00227	-0.0487***
		(0.00263)	(0.00561)	(0.00544)
	Carchi	-0.000880	-0.0104	-0.0563***
		(0.00541)	(0.00782)	(0.00870)
	Cotopaxi	-0.00246	-0.0167***	-0.0405***
		(0.00228)	(0.00393)	(0.00457)
	Chimborazo	0.000187	0.00903**	-0.0217***
		(0.00232)	(0.00454)	(0.00487)
	El Oro	-0.00843***	-0.0102***	-0.0250***
		(0.00116)	(0.00388)	(0.00486)
	Esmeraldas	-0.00195	-0.0285***	-0.0411***
		(0.00336)	(0.00426)	(0.00594)
	Guayas	-0.00390***	-0.0200***	-0.0239***
		(0.000988)	(0.00189)	(0.00283)
	Imbabura	0.00730***	0.00489	-0.0143***
		(0.00281)	(0.00442)	(0.00485)
	Loja	-0.00406**	-0.00889**	-0.0108**
		(0.00173)	(0.00416)	(0.00546)
	Los Ríos	0.00231	-0.0108**	-0.0422***
		(0.00290)	(0.00422)	(0.00458)
	Manabí	-0.00370**	-0.0141***	-0.0263***
		(0.00150)	(0.00306)	(0.00414)
	Morona Santiago	-	-0.00200	-0.0310***
			(0.00815)	(0.00836)
	Napo	0.00214	-0.00644	-0.00854
		(0.00690)	(0.0118)	(0.0152)
	Pastaza	3.91e-05	-0.0241***	-0.0308***
		(0.00659)	(0.00660)	(0.0110)
	Tungurahua	-0.000774	-0.00144	-0.0320***
		(0.00162)	(0.00319)	(0.00344)
	Zamora	0.00309	-0.0276***	-0.0432***
		(0.00754)	(0.00816)	(0.0106)
	Galápagos	-	-0.00860	0.00320
			(0.0134)	(0.0241)
	Sucumbíos	0.00240	-0.0140**	-0.0223**
		(0.00604)	(0.00699)	(0.00997)
	Orellana	-0.00334	-0.00138	-0.0302***
		(0.00425)	(0.0111)	(0.0113)
	Santo Domingo	0.000955	-0.00977**	-0.0289***
		(0.00253)	(0.00428)	(0.00499)
	Santa Elena	-	-0.0130**	-0.0457***
			(0.00645)	(0.00701)
Manufacturing Industry	Textiles	-0.00124	-0.00129	0.0619***
		(0.00119)	(0.00263)	(0.00526)
	Leather and shoes	-0.000412	0.00229	0.0456***
		(0.00221)	(0.00498)	(0.00947)

		(1) R&D	(2) Training	(3) ICT
	Wood and paper	-0.00159	0.00198	0.158***
		(0.00137)	(0.00324)	(0.00852)
	Chemicals	0.0134***	0.0234***	0.113***
		(0.00440)	(0.00851)	(0.0219)
	Rubber and plastic	0.00165	0.0183**	0.165***
		(0.00269)	(0.00777)	(0.0221)
	Non-metallic prod.	-0.00349**	-0.00340	0.0196***
		(0.00148)	(0.00387)	(0.00687)
	Furniture	-0.00151	0.00149	0.0457***
		(0.00126)	(0.00299)	(0.00554)
	Metallic products	-0.00127	0.00280	0.0573***
		(0.00133)	(0.00309)	(0.00581)
	Off. mach.-elect. equ.	0.0108***	0.00838	0.110***
		(0.00411)	(0.00684)	(0.0162)
	Communi./prec./med.	0.0208**	0.0663***	0.106***
		(0.00901)	(0.0177)	(0.0246)
	Transport equipment	-0.00141	0.0140	0.0712***
		(0.00274)	(0.00865)	(0.0167)
Legal form	Non-profit company	-	0.0319	0.0145
			(0.0304)	(0.0334)
	Private company	0.00124	0.0189***	0.0778***
		(0.00153)	(0.00507)	(0.0101)
	Foreign company	-	0.102	-
			(0.102)	
	Public company	0.0167	-0.000858	-0.00512
		(0.0134)	(0.0166)	(0.0305)
	Local Gove. company	-	-	-0.0226
				(0.0293)
	Cooperative	0.00615	0.0528	0.182*
		(0.0150)	(0.0659)	(0.0994)
	Association	0.00500	0.0461**	-0.00109
		(0.00646)	(0.0222)	(0.0154)
Professionaliz.	Enterprise network	0.00742***	0.0443***	0.0982***
		(0.00129)	(0.00310)	(0.00437)
	Market research	0.0356***	0.0753***	0.0750***
		(0.00450)	(0.00845)	(0.0101)
	Accountancy	0.0119***	0.0379***	0.123***
		(0.00223)	(0.00467)	(0.00749)
	Access to finance	0.00440***	0.0156***	0.0165***
		(0.000961)	(0.00203)	(0.00263)
	Environment	0.0205***	0.0951***	0.0710***
		(0.00376)	(0.0106)	(0.0117)
Other controls	Main custom. foreign	0.00330	0.00825	0.0494**
		(0.00282)	(0.00821)	(0.0217)
	Craft certification	-0.000617	0.00374*	-0.00809***
		(0.00100)	(0.00204)	(0.00261)
	Own local	-0.000476	-0.00246	-0.0105***
		(0.000858)	(0.00171)	(0.00228)
	Mother company	-0.000400	0.00974**	0.0200***
		(0.00130)	(0.00386)	(0.00610)
	Male manager	0.000911	-0.00366*	-0.0111***
		(0.000996)	(0.00215)	(0.00293)
	Log workers	0.00408***	0.0138***	0.0669***
		(0.000896)	(0.00196)	(0.00292)
	$(\text{Log workers})^2$	-0.000350**	4.37e-05	-0.00637***
		(0.000147)	(0.000408)	(0.000784)
	Log age	0.00127	0.0110***	0.0135***
		(0.00124)	(0.00271)	(0.00360)

	(1) R&D	(2) Training	(3) ICT
(Log age)^2	-0.000397	-0.00307***	-0.00330***
	(0.000320)	(0.000716)	(0.000935)
Constant	-3.146***	-2.432***	-2.554***
	(0.098)	(0.057)	(0.050)
Observations	42,292	42,292	42,292
Log pseudo-likelihood		-14207.293	
Correlation coefficients		ρ_{12} = 0.435, *p*-val.=0.000; ρ_{13} = 0.339, *p*-val.=0.000; ρ_{23} = 0.332, *p*-val.=0.000	

Notes:
1. Robust standard errors in parenthesis.
2. *** p<0.01, ** p<0.05, * p<0.1.
3. dy/dx for dummy variables is the discrete change from the 0 to the 1 category.

2.4.2 Firms' investments: R&D and workers training (Bivariate *Heckman*)

Let $y^*_{2i,j}$ (*j*=R&D or WT) denote the firm's latent R&D effort or workers training intensity, which are defined as the *log* of the annual expenditure *per* employee in R&D or workers training. These two latent innovation intensities are formally modelled as

(4) $y^*_{2i,j} = \beta^{'}_{2,j} x_{2i} + \varepsilon_{2i,j}$,

where $\beta^{'}_{2,j}$ captures the effects of explanatory variables on the potential innovation intensity *j* and $\varepsilon_{2i,j}$ denotes idiosyncratic errors that affect $y^*_{2i,j}$. The observed counterparts to $y^*_{2i,j}$ are defined as

(5) $y_{2i,j} = \mathbf{1}\left[y^*_{1i,j} > 0\right] y^*_{2i,j} \equiv y_{1i,j} \cdot y^*_{2i,j}$,

where $\mathbf{1}[\ ]$ again denotes the indicator function taking the value one if the condition between squared brackets is satisfied, and zero otherwise. This notation reflects that R&D or workers training intensities of firm *i* are observed to be positive only if firm *i* performs R&D or workers training activities, respectively ($y_{1i,j} = 1$, see equations (2) and (3) above). In estimation, we both allow for correlation of firm idiosyncratic error terms of each innovation intensity equation and its corresponding associated dichotomous decision (that is, correlation of $\varepsilon_{2i,j}$ in (4) with $\varepsilon_{1i,j}$ in (2)) and for correlation between idiosyncratic error terms in the two innovation intensity equations (that is, correlation between $\varepsilon_{2i,R\&D}$ and $\varepsilon_{2i,WT}$). We, hence, recognize that not only the discrete choice firms' decisions about performing R&D and training activities might be interrelated, but also their expenditures counterparts. For computational and convergence purposes we follow a two steps estimation procedure. In the first step, we use the estimated coefficients from the trivariate *probit* model to construct two Heckman's lambda terms (also called inverse Mill's ratios) that are used in the second step for sample selection bias correction in the estimation of two equations, one for the *log* of R&D intensity and another for the *log* of workers training intensity. In the second step, the two innovation intensity equations corrected for sample selection bias are jointly estimated with the Stata command *cmp* (Roodman, 2011) by pseudo-simulated maximum likelihood (PSML). As this procedure, besides corrections for sample selection, also allows for a non-zero correlation between the two innovation expenditure intensities error terms, we call it in this chapter a bivariate *Heckman*.[8] This two steps Heckman procedure allows for consistent estimation of parameters in the R&D and workers training intensity equations that can be extrapolated to population in spite of being estimated with the subpopulation of R&D or workers training performing firms, respectively (Heckman, 1979). This is a suitable method with our data since there are many manufacturing firms in Ecuador not performing R&D and/or not performing workers training activities. The implemented method will allow testing for the presence of sample selection in each one of the two intensity equations involved and also for the interrelation between firms' expenditures in R&D and workers training.

[8] Notice that the lambda terms have been calculated from coefficient estimates coming from a trivariate *probit* and, therefore, the lambda terms implicitly acknowledge that there exists a positive correlation between the R&D and workers training dichotomous firms' decisions.

The explanatory variables in x_{2i} are the same than in x_{1i} with the exception of the variable *log* workers squared, which is not included in the vector x_{2i}. This exclusion restriction will contribute to identification in the innovation intensity equations. Notice that, although we use as dependent variables in these equations the *log* of innovation expenditures per worker, the variable size (*log* workers) is included in these equations to let innovation expenditures not being necessarily proportional to size.

Estimation results for the innovation intensity equations are presented in Table C2.3. At the end of the table we have the estimated coefficients associated with the Heckman's lambda term for R&D sample selection correction in the R&D intensity equation and with the Heckman's lambda term for workers training sample selection correction in the workers training intensity equation. The two coefficients are positive and statistically significant, indicating, on the one side, that it was relevant to use sample selection methods for estimation instead of simple Ordinary Least Squares with the subsamples of R&D or workers training performers and, on the other side, that unobserved factors that increase firms' propensities to invest in R&D and workers training activities are positively correlated with their R&D and workers training investment intensities. Therefore, endogenous selection of firms into these activities was an issue to take care of. Furthermore, at the bottom of Table C2.3 we also present information about the correlation coefficient between the error terms in the two innovation intensity equations. The null hypothesis of $\rho_{R\&D,WT}=0$ is rejected ($\rho_{R\&D,WT}$=0.535, with *p-value*=0.000). Hence, there is a positive and statistically significant correlation between firms' R&D and workers training expenditures. This finding supports the use of the bivariate Heckman estimation procedure.

In column 1 of Table C2.3 we present the results for the R&D intensity equation and in column 2 for the workers training intensity equation. It is interesting to notice that all the variables in the group of professionalization and good business practices explain, with positive and statistically significant coefficients, higher intensity in both R&D and workers training investments. The variables in this group are: belonging to an Enterprise network or business group, performing Market research studies, accountancy, to be concerned about environmental issues, and to have Access to finance. Beyond indicating firms' good business practices, variables such as belonging to a business group or declaring access to finance might be indicative of lack of financial constraints to carry out these investments. Similarly, the performance of market research activities might point out deficiencies in demand that are responded with firms' innovation investments (specially with R&D).

Additionally, for the group of Other controls in the R&D intensity equation, we find that for older firms there is a negative effect of age and, more interestingly, a positive effect of Main customer being foreigner. For the workers training intensity equation, we obtain that larger firms have a lower intensity, while the opposite happens for firms with a Male manager, Mother companies, and firms which Main customer is a foreigner. There seems again that competition in international markets exerts pressure on firms' innovation efforts.

The location variables that are positive and statistically significant with respect to the reference category (Pichincha) in the R&D intensity equation are Carchi, Napo and Zamora. For the workers training intensity equation they are Imbabura, Napo, Zamora, Galápagos and Orellana. The ones that are negative and statistically significant for R&D are El Oro, Guayas, Loja, Manabí and Orellana. For the workers training equation they are Azuay, Chimborazo, Loja, Los Ríos and Pastaza. As regards industries, the ones justifying higher R&D intensities are Chemicals; Rubber and plastic; Office machinery and electrical equipment; and Communication, precision, medical and optical equipment. Fort the case of workers training intensities they are Chemicals, and Communication, precision, medical and optical equipment (and the ones with the lowest intensities, Textiles and Furniture). With respect to legal forms, most of them are positive and statistically significantly associated to both expenditures as regards the reference category (individual firms). This applies to Private and Public companies, Cooperatives and Associations, for R&D intensity, and to Private, Foreign and Cooperatives, for workers training intensity. For R&D intensity the highest coefficient is found for Public companies and for workers training intensity for Foreign companies.

Table C2. 3 Firm' investment: R&D and Training (Bivariate *Heckman*)

		(1)	(2)
	Variables	R&D intensity	Training intensity
Geographical location	Azuay	0.194	-0.233**
		(0.259)	(0.103)
	Bolívar	0.300	0.456
		(0.427)	(0.498)
	Cañar	-1.632	-0.381
		-1.274	(0.265)
	Carchi	0.845**	-0.080
		(0.369)	(0.428)
	Cotopaxi	-0.614	-0.189
		(0.561)	(0.245)
	Chimborazo	-0.672*	-0.309*
		(0.390)	(0.172)
	El Oro	-4.531***	-0.028
		(0.875)	(0.171)
	Esmeraldas	-0.099	-0.530
		(0.854)	(0.516)
	Guayas	-0.748**	0.005
		(0.295)	(0.132)
	Imbabura	0.669	0.235*
		(0.466)	(0.138)
	Loja	-1.638**	-0.603**
		(0.663)	(0.240)
	Los Ríos	-0.405	-0.459**
		(0.570)	(0.208)
	Manabí	-0.775*	-0.379
		(0.407)	(0.234)
	Morona Santiago	-	-0.264
			(0.494)
	Napo	0.798*	0.941**
		(0.448)	(0.370)
	Pastaza	0.279	-0.539**
		(0.333)	(0.256)
	Tungurahua	-0.430	0.138
		(0.346)	(0.121)
	Zamora	0.864*	0.557**
		(0.448)	(0.255)

		(1)	(2)
	Variables	R&D intensity	Training intensity
	Galápagos	-	0.971***
			(0.158)
	Sucumbíos	-0.736	0.017
		-1.189	(0.395)
	Orellana	-1.223***	1.572**
		(0.379)	(0.632)
	Santo Domingo	-0.104	-0.274
		(0.320)	(0.225)
	Santa Elena	-	0.195
			(0.536)
Manufacturing Indus.	Textiles	-0.377	-0.180*
		(0.260)	(0.099)
	Leather and shoes	0.330	-0.124
		(0.441)	(0.172)
	Wood and paper	0.027	-0.043
		(0.375)	(0.123)
	Chemicals	1.791***	0.452**
		(0.456)	(0.204)
	Rubber and plastic	1.141***	-0.013
		(0.361)	(0.167)
	Non-metallic prod.	-0.168	0.097
		(0.390)	(0.150)
	Furniture	-0.095	-0.203*
		(0.327)	(0.111)
	Metallic products	0.249	0.098
		(0.322)	(0.123)
	Off. mach.-elect. equ.	1.684***	0.238
		(0.499)	(0.186)
	Communi./prec./med.	1.635***	0.719**
		(0.626)	(0.301)
	Transport equipment	0.601	0.279
		(0.566)	(0.228)
Legal form	Non-profit company	-	-0.554
			(0.495)
	Private company	0.873***	0.385***
		(0.225)	(0.121)
	Foreign company	-	1.985***
			(0.617)
	Public company	3.071**	0.660
		-1.239	-1.319
	Cooperative	1.526*	1.317**
		(0.888)	(0.612)
	Association	1.126***	0.410
		(0.418)	(0.343)
Professionaliz.	Enterprise network	1.327***	0.547***
		(0.372)	(0.157)
	Market research	2.783***	0.691***
		(0.695)	(0.167)
	Accountancy	2.198***	0.719***
		(0.517)	(0.149)
	Access to finance	0.569***	0.247***
		(0.216)	(0.080)
	Environment	1.695***	0.564***
		(0.501)	(0.177)
Other controls	Main custom. foreign	0.524*	0.344*
		(0.315)	(0.180)
	Craft certification	0.036	-0.068
		(0.217)	(0.078)

	(1)	(2)
Variables	R&D intensity	Training intensity
Own local	-0.072	0.001
	(0.161)	(0.068)
Mother company	-0.165	0.507***
	(0.244)	(0.100)
Male manager	0.312	0.151*
	(0.214)	(0.083)
Log workers	-0.062	-0.396***
	(0.114)	(0.062)
Log age	0.501	-0.024
	(0.321)	(0.133)
(Log age)^2	-0.150**	0.013
	(0.075)	(0.033)
Lambda R&D	3.123***	
	(0.902)	
Lambda training		0.812***
		(0.295)
Constant	-5.745*	2.592***
	-3.022	(0.816)
Observations	412	1828
Log pseudo-likelihood	-3,833.363	
Correlation coefficient	$\rho_{R\&D,WT}$ = 0.535, p-val.=0.000	

Notes:
1. Robust standard errors in parenthesis.
2. *** p<0.01, ** p<0.05, * p<0.1.

2.4.3 Firms' productivity, R&D/training investments and ICT choices

There are very flexible methods for estimation of firms' productivity that require panel data availability. These are, for instance, the semi-parametric methods developed by Olley and Pakes (1996), Levinsohn and Petrin (2003), or Wooldridge (2009). However, the cross-sectional nature of our data prevents us from using these methods. For robustness of results, we will use in this chapter three productivity measures. The first one is the standard one of labour productivity, calculated as the *log* of sales *per* worker. The second one relies on estimation of a *Cobb-Douglas* production function. The third one on estimation of a *Translog* production function. The second and third measures proxy total factor productivity (TFP) by the estimated residual of the corresponding production functions, where firms' output is measured by *log* sales and firms' inputs by *log* number of workers, *log* capital (stock at book values of tangible fixed assets) and *log* materials.[9] At this estimation stage in the chapter, the three alternative measures of productivity will be our dependent variables on a set of regressions to uncover the role of our main variables of interest (R&D and workers training investments and ICT use) on TFP. In these regressions we will also control for firms' geographical location, industries, legal forms and other controls. Some of the controls may vary depending on the approach for productivity.[10] The results for the productivity regressions are presented in Table C2.4. Column 1 in this table is for the *log* labour productivity regression. This is a *log* linear productivity regression relating labour productivity to labour and its squared (i.e., we do not assume a constant scale elasticity), age and its squared, capital *per* worker, materials *per* worker, performance of Market research studies, the presence of a foreign main customer, and innovation activities. The regression in column 1 is the only one in Table C2.4 that includes capital and materials intensities. The reason is that since the dependent variable in this case is labour productivity, controlling for capital and materials intensities facilitates results from estimation to be interpreted as total factor productivity (TFP) effects (Crépon *et al.*, 1998). Innovation activities are captured, at first, by latent innovation (i.e. the potential

[9] The *Cobb-Douglas* and the *Translog* production functions are estimated for each one of the 12 industries. In the *Cobb-Douglas* production function, the average elasticity for materials (βm) is 0.58, for labour (βl) 0.39 and for capital (βk) 0.12. In the *Translog* production function, the average elasticity for materials (βm) is 0.58, for labour (βl) 0.36 and for capital (βk) 0.11.

[10] In a recent survey on TFP estimation, Van Beveren (2012) performs an empirical evaluation of TFP estimation methods as regards yielding different conclusions when conducting policy or impact evaluations (e.g. trade liberalization, deregulation, etc.). He shows that comparing OLS estimates with more sophisticated methods available for panel data that correct for potential simultaneity bias in input choices, high correlations between different estimated TFP measures emerge (higher than 0.8 or 0.95 depending on the methods) and, more importantly for us, similar conclusions are obtained when evaluating the effect of some policy change with different TFP measures.

R&D and workers training intensities and the propensity to use ICT). Thus, we can write

(6) $y_{3i} = \beta_3^{'} x_{3i} + \gamma_{3j} y_{i,j}^{*} + \varepsilon_{3i}$,

where γ_{3j} is a vector of three elements associated with the potential innovation intensities $y_{2i,j}^{*}$ in (4), with *j*=1 or 2 being referred to R&D or workers training, respectively, and with the potential ICT propensity, $P\left(y_{1i,j}=1\right)=P\left(y_{1i,j}^{*}>0\right)$ in (2)-(3), with *j*=ICT. The coefficients γ_{3j} capture the effects of innovation activities on productivity, $\beta_3^{'}$ captures the effect of all the other explanatory variables and controls in the regression for productivity, and ε_{3i} denotes idiosyncratic errors. To work in (6) with two estimated intensities (for R&D and workers training) and one estimated propensity (for ICT use) allows taking endogeneity concerns of innovation variables in the productivity equation into account. For instance, more productive firms might raise both more internal and external funding for innovation, implying reverse causality from productivity to innovation and, therefore, simultaneity bias. Furthermore, innovation variables could be affected by measurement errors specially affecting innovative expenditures. Though, instead of using predicted regressors for innovation to correct for endogeneity (i.e. the predicted R&D and workers training intensities and the predicted probability of ICT use), in this chapter we use the equivalent method of substituting predicted regressors by their observed value and the estimated residual calculated as the difference between their observed value and their predicted value (control function approach; see Wooldridge, 2010). In this way, the included estimated residuals not only clean coefficients from observed values of endogeneity bias, but also deliver coefficient estimates for the residuals, which statistical significance provides tests of endogeneity for the innovation variables. Both equivalent procedures are a sensible way to instrument innovation in the productivity equation.[11]

In columns 2 and 3 of Table C2.4 we present results for the residual TFP from Cobb-Douglas and Translog production functions, respectively. Our main interest from the productivity regressions is the estimation of elasticities for the R&D and workers training intensities and the corresponding semi-elasticity for ICT use. These magnitudes appear at the top of Table C2.4, and the coefficient estimates for their associated residual terms at the bottom of that table.[12] Results in Table C2.4 indicate that all residuals are negative and highly statistically significant, indicating not only the convenience of correcting for endogeneity as regards innovation variables in the productivity equations, but also the very likely presence of measurement errors in innovation variables, since the negative sign of coefficients for residuals is a signal of attenuation bias. The estimated elasticity for R&D intensity ranges from 0.049 (using the *Translog* TFP) to 0.061 (using labour productivity). From workers training intensity it goes from 0.059 (in the *Translog* case) to 0.111 (with labour productivity). The estimated semi-elasticity for ICT use indicates that using ICT increases TFP in a range from 34.0% (with the *Translog*) to 40.1% (with labour productivity). Estimated values for the *Cobb-Douglas* TFP regression are always in between and quite close to the *Translog* ones.

Among the group of Other controls in the productivity regressions, there were two variables included to control for demand factors and competition. These variables are

[11] Table C2.4 presents robust bootstrapped standard errors from 500 replications.

[12] Estimated residuals for the two innovation intensity variables come from the bivariate *Heckman* in section 2.4.2. The estimated residual for the ICT dichotomous decision comes from the difference between $y_{1i,ICT} - P\left(y^{*}_{1i,ICT} > 0\right)$ obtained from results in section 2.4.1.

whether the firm invests in Market research and whether the firm's main customer is foreigner. The second variable is never statistically significant (although with positive sign), giving support to our thought about this variable not really isolating exporters from non-exporters (notice that one firm can be an exporting firm without its main customer being foreigner). The first variable has a negative sign and it is statistically significant at the 10% level in the labour productivity regression. For the *Cobb-Douglas* and *Translog* TFP regressions the coefficient is still negative but closer to be significant (with a *p*-value of 12% and 13%, respectively). Obtained results for this variable are in favour of the Market research dummy to be an indicator for the firm's demand conditions. In particular, it can proxy for bad demand conditions that require Market research. Since we are working with "revenue" productivity and not with "physical" productivity, a downturn in demand puts pressure on firms' prices to go down and, therefore, "revenue" productivity decreases. The inclusion of this variable is relevant to clean the effects of other variables from demand conditions, which can affect "revenue" productivity through output prices instead of through efficiency.[13, 14]

For the variables age and size, we obtain that firms' age explains higher productivity but at a decreasing rate and, differently, there is not a clear result for firms' size. According to the labour productivity regression, there is a positive and linear relationship between firms' size and productivity. However, according to the *Cobb-Douglas* and *Translog* TFP regressions, larger firms, conditioning to anything else being equal, seem to be less productive.

[13] Firms' individual prices would be required for "physical" productivity, and they are commonly absent in most of the datasets.

[14] If we had a proper export dummy in our dataset, it could also contain relevant demand side information when firm prices are set differently in domestic than in export markets (see Aw *et al.*, 2011, and Máñez *et al.*, 2015, among others).

As regards geographical location of firms, most of the provinces show a lower productivity than the reference category, Pichincha. Exceptions are El Oro, Los Ríos, Galápagos, Sucumbíos, Orellana and Santo Domingo, with similar productivity to Pichincha. Sectors with lower productivity than the reference category, Food, drinks and tobacco, are clearly Wood and paper, Rubber and plastic, and Metallic products. Others are only negative and statistically significant in two out of three of the productivity regressions. This is the case for Non-metallic products, Furniture, and Office machinery and electrical equipment. The only sector with a higher productivity than the reference category seems to be Chemicals (and this happens only for two of the three productivity regressions). With respect to legal forms, the one with higher associated productivity is Private Company (in two of the three productivity regressions). The ones with lower are Non-profit Company, Credit and Saving cooperatives (the ones that perform manufacturing activities) and, sometimes, Association. The reference category corresponds to natural person companies.

Table C2. 4 Firms' productivity, R&D/Training investments and ICT choices.

		(1)	(2)	(3)
	Variables	**Log Labour Productivity**	**Cobb-Douglas Total Factor Productivity**	**Translog Total Factor Productivity**
	Log R&D intensity	0.061**	0.050**	0.049**
		(0.024)	(0.023)	(0.024)
	Log Training intensity	0.111***	0.077***	0.059**
		(0.029)	(0.027)	(0.027)
	ICT use	0.401***	0.346***	0.340***
		(0.051)	(0.056)	(0.050)
Geographical location	Azuay	-0.172***	-0.165***	-0.166***
		(0.015)	(0.014)	(0.015)
	Bolívar	-0.222***	-0.184***	-0.191***
		(0.043)	(0.044)	(0.041)
	Cañar	-0.091***	-0.104***	-0.124***
		(0.029)	(0.031)	(0.029)
	Carchi	-0.242***	-0.222***	-0.235***
		(0.042)	(0.044)	(0.039)
	Cotopaxi	-0.173***	-0.171***	-0.165***
		(0.020)	(0.020)	(0.021)
	Chimborazo	-0.158***	-0.168***	-0.182***
		(0.023)	(0.025)	(0.024)
	El Oro	0.013	0.004	0.002
		(0.039)	(0.039)	(0.039)
	Esmeraldas	-0.086***	-0.074**	-0.095***
		(0.026)	(0.029)	(0.025)
	Guayas	-0.057***	-0.038***	-0.045***
		(0.013)	(0.014)	(0.013)
	Imbabura	-0.205***	-0.195***	-0.172***
		(0.020)	(0.020)	(0.019)
	Loja	-0.033	-0.049*	-0.065**
		(0.024)	(0.026)	(0.026)
	Los Ríos	0.039	0.039	0.009
		(0.026)	(0.028)	(0.025)
	Manabí	-0.175***	-0.164***	-0.181***
		(0.017)	(0.015)	(0.016)
	Morona Santiago	-0.094***	-0.112***	-0.116***
		(0.032)	(0.030)	(0.031)
	Napo	-0.178***	-0.154***	-0.133**
		(0.049)	(0.054)	(0.052)
	Pastaza	-0.210***	-0.218***	-0.223***
		(0.039)	(0.043)	(0.043)
	Tungurahua	-0.174***	-0.175***	-0.166***
		(0.018)	(0.017)	(0.017)
	Zamora	-0.321***	-0.296***	-0.272***
		(0.044)	(0.042)	(0.040)
	Galápagos	0.124	0.141	0.140
		(0.099)	(0.105)	(0.102)
	Sucumbíos	-0.023	-0.031	-0.019
		(0.047)	(0.043)	(0.040)
	Orellana	-0.047	-0.011	0.018
		(0.066)	(0.063)	(0.062)
	Santo Domingo	0.034	0.035	0.022
		(0.021)	(0.022)	(0.021)
	Santa Elena	-0.191***	-0.157***	-0.160***
		(0.028)	(0.026)	(0.027)
	Unfenced areas	-0.258***	-0.244**	-0.245***
		(0.090)	(0.098)	(0.091)

		(1)	(2)	(3)
	Variables	**Log Labour Productivity**	**Cobb-Douglas Total Factor Productivity**	**Translog Total Factor Productivity**
Manufacturing Industry	Textiles	-0.017	0.014	0.005
		(0.013)	(0.013)	(0.011)
	Leather and shoes	-0.058**	-0.029	0.007
		(0.025)	(0.024)	(0.022)
	Wood and paper	-0.161***	-0.134***	-0.060***
		(0.017)	(0.016)	(0.014)
	Chemicals	0.094**	0.128**	-0.221***
		(0.047)	(0.050)	(0.047)
	Rubber and plastic	-0.099**	-0.077*	-0.164***
		(0.045)	(0.046)	(0.044)
	Non-metallic prod.	-0.075***	-0.040**	0.000
		(0.022)	(0.020)	(0.020)
	Furniture	-0.094***	-0.079***	-0.009
		(0.013)	(0.013)	(0.013)
	Metallic products	-0.117***	-0.093***	-0.051***
		(0.014)	(0.016)	(0.015)
	Off. mach.-elect. equ.	-0.061*	-0.049	-0.095***
		(0.032)	(0.033)	(0.029)
	Communi./prec./med.	-0.069	-0.040	-0.073
		(0.046)	(0.047)	(0.045)
	Transport equipment	-0.059	-0.043	-0.072*
		(0.041)	(0.041)	(0.039)
Legal form	Non-profit company	-0.308**	-0.331**	-0.454**
		(0.152)	(0.165)	(0.186)
	Private company	0.091**	0.091**	-0.000
		(0.036)	(0.037)	(0.034)
	Foreign company	0.054	0.065	-0.155
		(0.319)	(0.329)	(0.198)
	Public company	0.356	0.412	0.145
		(0.262)	(0.273)	(0.158)
	Local Gove. company	0.393	0.410	-0.180
		(0.707)	(0.628)	(0.463)
	Credit/Saving Coop.	-0.535***	-0.584***	-0.845***
		(0.069)	(0.068)	(0.063)
	Cooperative	-0.050	0.005	-0.031
		(0.209)	(0.194)	(0.250)
	Association	-0.148	-0.127	-0.216*
		(0.098)	(0.095)	(0.110)
Other controls	Market research	-0.047*	-0.038†	-0.035††
		(0.026)	(0.025)	(0.023)
	Main custom. foreign	0.038	0.038	0.023
		(0.056)	(0.061)	(0.053)
	Log workers	0.084***	-0.046*	0.020
		(0.021)	(0.025)	(0.024)
	$(\text{Log workers})^2$	0.000	-0.000	-0.013***
		(0.003)	(0.003)	(0.003)
	Log age	0.082***	0.070***	0.076***
		(0.013)	(0.012)	(0.013)
	$(\text{Log age})^2$	-0.020***	-0.017***	-0.019***
		(0.004)	(0.003)	(0.004)
	Log capital per worker	0.104***		
		(0.003)		
	Log mater. per worker	0.563***		
		(0.004)		
	Constant	2.914***	-0.485***	-0.483***
		(0.148)	(0.161)	(0.160)
	Resid. LogR&D inten.[3]	-0.059***	-0.048**	-0.051**
		(0.023)	(0.023)	(0.023)

Variables	(1) Log Labour Productivity	(2) Cobb-Douglas Total Factor Productivity	(3) Translog Total Factor Productivity
Resid. Log Trai. inten.[3]	-0.099***	-0.069***	-0.055**
	(0.028)	(0.027)	(0.027)
Resid. ICT use[3]	-0.275***	-0.249***	-0.237***
	(0.051)	(0.058)	(0.052)
Observations	41,665	41,665	41,665
R-squared	0.627	0.040	0.030

Notes:
1. Robust bootstrapped standard errors in parenthesis (500 replications).
2. *** p<0.01, ** p<0.05, * p<0.1.
3. Residual terms from the previously estimated R&D intensity, Training intensity and ICT use equations, respectively. These terms correct for endogeneity of R&D and Training intensities and ICT use in the productivity equations.
4. Since the dependent variables are in logs, coefficient estimates for explanatory variables that are in logs are to be interpreted as elasticities. Those for dummy variables have the interpretation of semielasticities.
5. † indicates with *p*-value equal to 12%. †† indicates with *p*-value equal to 13%.

2.4.4 Firms' markups (from *Translog* production function), R&D/training investments and ICT choices

We estimate firm specific markups (defined as the ratio of the price over marginal cost) following De Loecker and Warzynski (2012) as:

(7) $\mu_{is} = e_{is}^{X} / sh_{i}^{X}$,

where μ_{is} is the markup of firm *i* in industry *s*, e_{is}^{X} is the output elasticity of variable input *X* (obtained for each one of the 12 considered industries) and sh_{i}^{X} is the firm's revenue share of variable input *X*. The revenue share of variable input *X* is defined as the total cost of that input over firm's total sales.

The only assumptions imposed by this methodology are firms' cost minimization and the presence of freely adjustable inputs. There is no need to make assumptions about the mode of competition or the functional form of demand. Notice that this methodology only requires firms' production data to infer markups. The intuition behind is that under perfect competition, prices are equal to marginal costs and, hence, input choices of cost minimizer firms will make the revenue share to be equal to the output elasticity of the input. In this case, the value of the markup will be 1.

However, under imperfect competition, the revenue shares are lower than the output elasticities, which implies markups above 1 (prices above marginal costs).

According to this methodology only one variable input is required, and in our case the one chosen has been materials. We have a double reason for this choice. On the one hand, as the alternative variable input is labour, this production factor is more likely affected by adjustment costs than materials.[15] On the other hand, the dataset has many more missing values on the information of firms' wages than on the information about materials costs. Opting for the variable input labour will imply discarding a big proportion of the sample size used for estimation of total factor productivity measures. In particular, selecting materials as the freely adjustable input we can estimate the markups equation with 41,647 observations. Should we have selected labour the number of observations would have been only 16,763.

The denominator in (7), $sh_i^{Materials}$, can be directly computed with firms' ratios of materials costs over sales using the data available in the dataset. However, the output elasticity of the input materials has to be estimated from a production function. In the previous section (2.4.3) we have estimated both a *Cobb-Douglas* and a *Translog* production function. However, since the *Cobb-Douglas* restricts output elasticities of inputs to be constant for all firms in a given industry, we rely on the *Translog* estimates, which allow between firms' variation in markups both coming from the numerator and the denominator in (7).

[15] Adjustment costs drive a wedge between output elasticities and input revenue shares for different reasons than markups. This is the reason for which this literature does not consider the capital input to infer markups.

Expressed in natural logarithms, the previously estimated *Translog* production function in section (2.4.3) above was as follows:

(8) $Sales_{is} = \alpha_s + \beta_{ls} l_i + \beta_{ks} k_i + \beta_{ms} m_i + \beta_{ll,s} l_i^2 + \beta_{kk,s} k_i^2 + \beta_{mm,s} m_i^2 + \beta_{lk,s} l_i k_i + \beta_{lm,s} l_i m_i + \beta_{km,s} k_i m_i + tfp_{is}$,

From where the output elasticity of materials is computed as:

(9) $e_{is}^{Materials} = \beta_{ms} + 2\beta_{mm,s} m_i + \beta_{lm,s} l_i + \beta_{km,s} k_i$

Notice that the corresponding elasticity from a *Cobb-Douglas* would be only $e_{is}^{Materials} = \beta_{ms}$, since a *Cobb-Douglas* is nested in the *Translog* when $\beta_{ll,s}$, $\beta_{kk,s}$, $\beta_{mm,s}$, $\beta_{lk,s}$, $\beta_{lm,s}$, $\beta_{km,s}$ are equal to 0.

Again, similarly to the TFP regressions, in the markups regressions innovation activities depend on latent innovation (i.e. the potential R&D and workers training intensities and the propensity to use ICT). Thus, we can write

(10) $\log \mu_{is} = \beta_4^{'} x_{4i} + \gamma_{4j} y_{i,j}^{*} + \varepsilon_{4i}$,

where γ_{4j} is a vector of three elements associated with the potential innovation intensities $y_{2i,j}^{*}$ in (4), with *j*=1 or 2 being referred to R&D or workers training, respectively, and with the potential ICT propensity, $P\left(y_{1i,j} = 1\right) = P\left(y_{1i,j}^{*} > 0\right)$ in (2)-(3), with *j*=ICT. The coefficients γ_{4j} capture the effects of innovation activities on markups, $\beta_4^{'}$ captures the effect of all the other explanatory variables and controls in the regression for markups, and ε_{4i} denotes idiosyncratic errors. To work in (10) with two estimated intensities (for R&D and workers training) and one estimated propensity (for ICT use) allows taking endogeneity concerns of innovation variables in the markups equation into account. Markups can proxy for market power and, therefore, may influence firms' innovation decisions and investments. Additionally, innovation variables may suffer from measurement errors. Hence, estimation of equation (10) requires either using predicted regressors for innovation (i.e. the predicted R&D and workers training intensities and the predicted probability of ICT use) or, equivalently, substituting predicted regressors by their observed values and the estimated residual terms from the previously estimated R&D intensity, workers training intensity and ICT use equations. The latter is the (control function-) approach we follow in this chapter, since not only the inclusion of the before mentioned predicted residuals corrects for endogeneity of R&D and workers training intensities and ICT use in the markups equation, but also allows testing for it. This is a way to instrument innovation in the markups equation.[16]

[16] Table C2.5 presents robust bootstrapped standard errors from 500 replications.

Table C2. 5 Firms' markups (from *translog* production function), R&D/Training investments and ICT choices

		(1)	(2)
	Variables	**Log Markup**	**Log Markup**
	Log R&D intensity	0.107***	0.048***
		(0.020)	(0.009)
	Log Training intensity	0.012**	0.041***
		(0.005)	(0.008)
	ICT use	0.419***	0.085***
		(0.046)	(0.017)
	Translog TFP		0.704***
			(0.043)
Geographical location	Azuay	-0.188***	-0.054***
		(0.014)	(0.010)
	Bolívar	-0.149***	-0.050***
		(0.039)	(0.010)
	Cañar	-0.085***	0.013**
		(0.027)	(0.006)
	Carchi	-0.287***	-0.103***
		(0.038)	(0.018)
	Cotopaxi	-0.154***	-0.049***
		(0.021)	(0.008)
	Chimborazo	-0.153***	-0.014*
		(0.021)	(0.008)
	El Oro	0.104***	0.053***
		(0.033)	(0.011)
	Esmeraldas	-0.092***	-0.007
		(0.028)	(0.006)
	Guayas	-0.029***	-0.014***
		(0.011)	(0.004)
	Imbabura	-0.165***	-0.065***
		(0.017)	(0.007)
	Loja	-0.042**	0.024***
		(0.020)	(0.005)
	Los Ríos	0.041*	0.037***
		(0.024)	(0.005)
	Manabí	-0.188***	-0.046***
		(0.016)	(0.009)
	Morona Santiago	-0.122***	-0.030***
		(0.028)	(0.010)
	Napo	-0.102**	-0.096***
		(0.041)	(0.013)
	Pastaza	-0.233***	-0.087***
		(0.045)	(0.017)
	Tungurahua	-0.135***	-0.047***
		(0.015)	(0.007)
	Zamora	-0.223***	-0.101***
		(0.029)	(0.014)
	Galápagos	0.251***	0.098***
		(0.092)	(0.022)
	Sucumbíos	0.063	0.045***
		(0.040)	(0.012)
	Orellana	0.142***	-0.001
		(0.043)	(0.018)
	Santo Domingo	0.038*	0.034***
		(0.021)	(0.004)
	Santa Elena	-0.142***	-0.061***
		(0.025)	(0.009)

		(1)	(2)
	Variables	**Log Markup**	**Log Markup**
	Unfenced areas	-0.244***	-0.113***
		(0.093)	(0.021)
Manufacturing Industry	Textiles	-0.043***	-0.009***
		(0.011)	(0.003)
	Leather and shoes	-0.058***	-0.020***
		(0.022)	(0.005)
	Wood and paper	-0.154***	-0.079***
		(0.015)	(0.005)
	Chemicals	0.076	0.243***
		(0.047)	(0.017)
	Rubber and plastic	-0.285***	-0.099***
		(0.045)	(0.015)
	Non-metallic prod.	-0.042**	-0.035***
		(0.019)	(0.005)
	Furniture	-0.069***	-0.034***
		(0.012)	(0.003)
	Metallic products	-0.178***	-0.127***
		(0.014)	(0.005)
	Off. mach.-elect. equ.	-0.117***	-0.038***
		(0.029)	(0.009)
	Communi./prec./med.	-0.161***	-0.123***
		(0.049)	(0.020)
	Transport equipment	-0.314***	-0.262***
		(0.041)	(0.020)
Legal form	Non-profit company	-0.428**	-0.077
		(0.179)	(0.049)
	Private company	0.030	0.075***
		(0.034)	(0.010)
	Foreign company	0.143	0.132
		(0.240)	(0.211)
	Public company	0.066	-0.007
		(0.207)	(0.060)
	Local Gove. company	-0.275	0.259***
		(0.443)	(0.026)
	Credit/Saving Coop.	-0.339***	0.214***
		(0.063)	(0.047)
	Cooperative	-0.023	-0.042
		(0.247)	(0.065)
	Association	-0.124	0.010
		(0.099)	(0.028)
Other controls	Market research	-0.040*	-0.012*
		(0.024)	(0.007)
	Main custom. foreign	0.021	0.042**
		(0.056)	(0.019)
	Log workers	0.191***	0.201***
		(0.015)	(0.006)
	Log capital	0.047***	-0.216***
		(0.003)	(0.002)
	Log material	-0.231***	0.061***
		(0.004)	(0.001)
	Constant	1.495***	1.331***
		(0.089)	(0.051)
	Resid. LogR&D inten.[3]	-0.107***	-0.048***
		(0.018)	(0.008)
	Resid. Log Trai. inten.[3]	-0.018	-0.033***
		(0.024)	(0.008)
	Resid. ICT use[3]	-0.293***	-0.050***
		(0.048)	(0.016)
	Resid. Translog TFP[4]		0.294***
			(0.044)

Variables	(1) Log Markup	(2) Log Markup
Observations	41,647	41,647
R-squared	0.151	0.968

Notes:
1. Robust bootstrapped standard errors in parenthesis (500 replications).
2. *** p<0.01, ** p<0.05, * p<0.1.
3. Residual terms from the previously estimated R&D intensity, Training intensity and ICT use equations, respectively. These terms correct for endogeneity of R&D and Training intensities and ICT use in the markup equation.
4. Residual term from the previously estimated TFP regression (using the *Translog* estimates) and taking into account innovation variables and other controls. This term corrects for endogeneity of TFP in the markup equation.
5. Since the dependent variables are in logs, coefficient estimates for explanatory variables that are in logs are to be interpreted as elasticities. Those for dummy variables have the interpretation of semielasticities.

In column 1 of Table C2.5 we present results for the estimation of our baseline markups equation in (10). Since the markups are in logs, coefficient estimates for explanatory variables that are in logs are to be interpreted as elasticities. Those for dummy variables have the interpretation of semi-elasticities. Column 2 of Table C2.5 augments the baseline equation in (10) by including also among regressors the *Translog* TFP. The estimated residual calculated as the difference between the *Translog* TFP and its prediction, which contains as regressors innovation variables and other controls, is also included in column 2 of Table C2.5. At the top of that table are the coefficient estimates for our innovation variables of interest in this chapter (and also that of the TFP in column 2). The coefficient estimates for their associated residual terms are presented at the bottom of the table. All the coefficients for residuals of innovation variables are negative and statistically significant (excluding the one for workers training intensity in column 1 that although negative is non-significant). This confirms both the convenience of correcting for endogeneity of innovation variables in the markups equations and also the likely presence of measurement errors in these variables, since the negative sign of coefficients for residuals is a signal of attenuation bias. Differently, the coefficient of the residual for TFP is positive and statistically significant (see column 2), indicating that the TFP regressor in the markups equation may suffer more from reverse causality bias than from attenuation bias coming from measurement errors. Is then also important to correct for endogeneity of this regressor.

According to results from column 1 of Table C2.5 we obtain that the estimated elasticity for R&D intensity is 0.107. For workers training intensity it is 0.012. The estimated semi-elasticity for ICT use indicates that using ICT justifies an increase in markups of 41.9%. Coefficients for R&D intensity and ICT use are roughly halved and much more than halved, respectively, when we control for productivity in the regression (column 2). This supports the idea that firms investing in R&D and using ICT charge higher markups because of two reasons: one being that they are also more productive and the other one probably related to the generation of other firms' advantages such as, for instance, higher quality products, allowing firms to charge higher prices. Considering TFP as a proxy for marginal costs (as in De Loecker and Warzynski, 2012), elasticities and semi-elasticities in column 2 of Table C2.5 would be net of the effect of variables on markups acting through the channel of productivity and, hence, they would pick up the effect on markups of these variables through the firm's capacity to fix prices above marginal costs. Therefore, the elasticity for R&D intensity and the semi-elasticity for ICT use are reduced in column 2 to values 0.048 and 8.5%, respectively. Comparing with the magnitudes from column 1, we see that roughly half of the effect of R&D intensity on markups acts through decreasing marginal costs, that is, increasing firm's efficiency. The other half accounts for the effect on higher firm's selling prices. For the case of ICT use, around one quarter of the effects are explained by higher prices and the rest by higher efficiency (lower marginal costs).

Something different happens to the elasticity of training intensity, which value increases in column 2 when controlling for TFP. Notice that, since $\log \mu_{is}$ can be written as the difference $\log P_{is} - \log TFP_{is}$, where P_{is} and TFP_{is} are, respectively, firm's prices and TFP (which proxies for marginal costs), the coefficient for workers training intensity in column (1) can be smaller than in column (2) if: workers training investments decrease marginal costs less than what they decrease prices (more than full pass-through from marginal costs reductions to reductions in prices). Finally, the TFP elasticity in the markups regression is 0.704.

Following De Loecker and Warzynski (2012), in the group of other controls we have included the three inputs in the production function. They recommend their inclusion in the markup regressions in order to eliminate a potential bias that may emerge in firm's investments coefficients when inputs are correlated with unobserved firm's output price variation. Furthermore, and similarly to the TFP regressions, we also include the variables Market research and whether the firm's Main customer is foreigner. They are included to capture demand shocks and market power affecting markups that could bias innovation coefficients in the markups equations (since not only markups depend on competition but also competition affects innovation investments).[17] The coefficient for Market research is negative and statistically significant, likely related to a lack of firm's demand that calls for market studies. However, the coefficient for Main customer being foreigner is positive and statistically significant only when controlling for TFP in the regression (column 2). The reason could be that among equally efficient firms, the ones with Main client being foreigner are able to charge higher prices.

[17] The reason is that revenue productivity still potentially captures differences in firms' prices. In any case, De Loecker and Warzynski (2012) show that using revenue productivity affects only the level of the markup estimates, and not the correlation between markups and firm-level characteristics.

Looking at variables of geographical location, most of the provinces present a lower markup than the reference category (Pichincha). Exceptions are El Oro, Los Ríos, Galápagos, Sucumbíos, Orellana and Santo Domingo. All the industries, with the exception of Chemicals, display lower markups than the reference category (Food, drinks and tobacco). There is not a clear pattern of markups as regards legal forms. It seems that the lowest markup is for Non-profit companies and the highest for Private and Local government companies.

2.5 Concluding remarks

The Ecuadorian economy is still heavily dependent on oil prices and agriculture. The Ecuadorian government is very much interested in transforming the economy into a more knowledge oriented one. This is particularly important for the manufacturing sector, where one of the expected relevant drivers of productivity is innovation. However, using the Economic Census of Ecuador (2010) for manufacturing firms, 88.34% of them are not involved in any of the three considered innovation activities in this chapter: R&D, workers training, and ICT use. But not only innovation can encourage firms' productivity, also can influence product and quality differentiation and, hence, justify higher prices. All this highlights that Ecuadorian manufacturing firms have not yet obtained all the benefits from innovation activities.

In this chapter, understanding that knowledge creation is multidimensional and includes investments in R&D and in human capital but also access to information and communications technology (ICT) to facilitate knowledge transfer, we are interested first in explaining firms' decisions about these investments. Our interest is not only about dichotomous decisions but also about amounts invested. Second, we are interested in the effects that innovation activities have on firms' productivity. Finally, we focus on the effects they also have on firms' markups.

As regards the questions raised up in the chapter, we can summarize results as follows. First, the variables included to signal professionalization and good business practices in Ecuadorian manufacturing firms, such as belonging to an enterprise network, having access to finance, performing activities of market research, accountancy, and having environmental concerns, explain both higher propensities to invest in R&D, workers training, and ICT use, and also higher R&D and workers training intensities (for ICT use the database does not contain information about amounts of investment).

Second, the three considered innovation activities have a positive and relevant effect on firms' TFP, with an estimated elasticity for R&D intensity around 0.05, for workers training intensity 0.06, and a semi-elasticity for ICT use that implies that performing this activity justifies around 34% higher TFP. Third, they are also relevant to explain higher firms' markups, since the statistically significant estimated elasticity for R&D intensity in the markups regression is around 0.11, for workers training intensity 0.01, and the semi-elasticity for ICT use justifies around 42% higher markups.

Additionally, the estimated markups regression that includes among regressors the variable TFP allows discerning whether innovation activities influence markups by affecting efficiency and/or by affecting firms' capacity to set prices. In particular, we obtain that around half of the effect of R&D intensity on markups acts through increasing firms' efficiency, and the other half through higher selling prices. For ICT, around three quarters are explained by higher efficiency and one quarter by higher prices. Innovation activities probably generate higher quality products. Interpretation of results for workers training investments is more complex, since it likely points out to a situation where there is more than full pass-through from marginal costs reductions to reductions in prices.

Worth mentioning are results for the variables Market research and Main customer being foreigner. The realization of market research activities by the firm are associated both to higher propensity to perform R&D and workers training investments and to higher intensity in these investments. This may point out some demand problems requiring innovations. This is reinforced by the fact that Market research is associated to lower markups in the markups regressions (demand conditions pressuring prices to go down). The positive association between Main customer being foreigner and R&D and workers training intensities may suggest that learning and competition from international markets encourages firms' innovation efforts. Its effect on markups is also positive, this time probably indicating that firms which main customer is foreigner are able to charge higher prices (likely related to better quality products).

As regards firms' geographical location, Pichincha is in general outperforming other Ecuadorian provinces in terms of R&D, workers training, ICT use, TFP, and markups. Furthermore, private company is the legal form associated with higher TFP and with higher markups (also local government companies are associated with higher markups).

From a policy point of view, the fact that firms belonging to a business group or declaring to have access to finance have both higher likelihoods to perform innovation activities and higher intensity in their investments, may point out to the relevance of easing Ecuadorian manufacturing firms' financial constraints in order to promote these activities. Spreading these activities among more manufacturing firms will promote both firms' productivity and markups and will contribute to counteract the threat of deceleration and slowdown in the Ecuadorian economy, making it stronger against drops in oil prices and U.S. dollar appreciations. This requires comprehensive policies encouraging not only R&D investments but also education and training on the job to increase skills, and extending ICT use, which facilities profiting from global networks of knowledge.

Appendix C2. 1 Industry classification

Industry	Description
Industry 1	Food, drinks and tobacco
Industry 2	Textiles
Industry 3	Leather and shoes
Industry 4	Wood and paper
Industry 5	Chemicals
Industry 6	Rubber and plastic
Industry 7	Non-metallic products
Industry 8	Furniture
Industry 9	Metallic products
Industry 10	Office machinery and electrical equipment
Industry 11	Communication, medical, precision and optimal equip.
Industry 12	Transport equipment

Appendix C2. 2 Variables Description

Variable	Description
R&D	Dummy variable taking value 1 if the firm does R&D activities, and 0 otherwise.
Workers training	Dummy variable taking value 1 if the firm performs training programs for the employees, and 0 otherwise.
ICT	Dummy variable taking value 1 if the firm uses Information and Communication Technologies, and 0 otherwise.
R&D intensity	Expenditure in R&D per employee.
Training intensity	Expenditure in training programs per employee.
Provinces	Dummy variables taking value 1 if the firm is located in a particular province, and 0 otherwise.
Industries	Dummy variables taking value 1 if the firm belongs to a particular industry, and 0 otherwise.
Natural person	Dummy variable taking value 1 if the business has a natural person recognition by the National Tax Service, and 0 otherwise.
Non-profit company	Dummy variable taking value 1 if the firm is a non-government, non-lucrative organization, and 0 otherwise.
Private company	Dummy variable taking value 1 if the firm is a private company, and 0 otherwise.
Foreign company	Dummy variable taking value 1 if the firm has foreign control, and 0 otherwise.
Public company	Dummy variable taking value 1 if the firm is under the central government control, and 0 otherwise.
Local Gove. company	Dummy variable taking value 1 if the firm is under the local government control, and 0 otherwise.
Cooperative	Dummy variable taking value 1 if the firm is a cooperative, and 0 otherwise.
Association	Dummy variable taking value 1 if the firm is considered an association, and 0 otherwise.
Enterprise network	Dummy variable taking value 1 if the firm is a member of an enterprise network or business group, and 0 otherwise.
Market research	Dummy variable taking value 1 if the firm does market research, and 0 otherwise.
Accountancy	Dummy variable taking value 1 if the firm has accounting control, and 0 otherwise.
Access to finance	Dummy variable taking value 1 if the firm has access to external finance, and 0 otherwise.
Environment	Dummy variable taking value 1 if the firm does some activity to improve the environment and has environmental concerns, and 0 otherwise.
Main custom. foreign	Dummy variable taking value 1 if the firm has a foreign main customer, and 0 otherwise.
Craft certification	Dummy variable taking value 1 if the firm has a Craft Certification, and 0 otherwise. It is giving by the government to "natural persons" (self-employed) whom demonstrate long experience (in years) with handmade or technician work (non-professional). The “natural persons” enjoy a tax benefit with this type of certification.
Own local	Dummy variable taking value 1 if the local of the firm is own by the firm, and 0 otherwise.
Mother company	Dummy variable taking value 1 if the firm is a mother company, and 0 otherwise.
Male manager	Dummy variable taking value 1 if the firm manager is a male, and 0 otherwise.
Log workers	Number of employees of the firm. This variable is in log form.
(Log workers)^2	Number of log employees squared.
Log age	Number of years since the firm was born. This variable is in log form.
(Log age)^2	Log age squared.
Log labour Producti.	Sales per employee in log form.
Coob-Douglas TFP	TFP in log form estimated from a Coob-Douglas production function.
Translog TFP	TFP in log form estimated from a Translog production function.
Log capital	Stock of tangible fixed assets at book values. This variable is in log form.
Log capital/worker	Capital per employee. This variable is in log form.
Log material	Amount of materials. This variable is in log form.
Log materials/worker	Materials per employee. This variable is in log form.
Markup	Defined as price over marginal cost. Estimated from firm production data and the labour elasticity from the Translog production function.

Appendix C2. 3 Descriptive statistics

Variable	Obs	Mean	Std. Dev.
R&D	42292	0.0097	0.0982
Workers training	42292	0.0432	0.2033
ICT	42292	0.0986	0.2982
Log R&D intensity	412	5.1555	1.7565
Log Training intensity	1828	4.3227	1.4649
Azuay	42292	0.1026	0.3034
Bolívar	42292	0.0080	0.0891
Cañar	42292	0.0194	0.1379
Carchi	42292	0.0078	0.0883
Cotopaxi	42292	0.0294	0.1690
Chimborazo	42292	0.0398	0.1955
El Oro	42292	0.0377	0.1905
Esmeraldas	42292	0.0166	0.1280
Guayas	42292	0.1887	0.3913
Imbabura	42292	0.0393	0.1944
Loja	42292	0.0382	0.1918
Los Ríos	42292	0.0292	0.1685
Manabí	42292	0.0561	0.2301
Morona Santiago	42292	0.0096	0.0977
Napo	42292	0.0046	0.0680
Pastaza	42292	0.0066	0.0815
Pichincha	42292	0.2388	0.4264
Tungurahua	42292	0.0605	0.2384
Zamora	42292	0.0069	0.0830
Galápagos	42292	0.0020	0.0447
Sucumbíos	42292	0.0078	0.0879
Orellana	42292	0.0050	0.0707
Santo Domingo	42292	0.0297	0.1698
Santa Elena	42292	0.0139	0.1170
Food, Beverage & Tab.	42292	0.2211	0.4150
Textiles	42292	0.2188	0.4134
Leather & Shoes	42292	0.0277	0.1642
Wood & Paper	42292	0.0998	0.2997
Chemicals & Petrol.	42292	0.0091	0.0949
Rubber & Plastic	42292	0.0111	0.1050
Glass & No metal.	42292	0.0578	0.2334
Furniture	42292	0.1602	0.3668
Metallic products	42292	0.1655	0.3716
Office, elect. & spec. mach.	42292	0.0129	0.1130
Communication	42292	0.0053	0.0730
Transport equipment	42292	0.0101	0.1002
Non-profit company	42292	0.0007	0.0270
Private company	42292	0.0364	0.1874
Foreign company	42292	0.0001	0.0119
Public company	42292	0.0008	0.0299
Local gov. company	42292	0.0005	0.0233
Cooperative	42292	0.0002	0.0153
Association	42292	0.0018	0.0426
Natural persons (Self-empl.)	42292	0.9591	0.1980
Enterprise network	42292	0.1914	0.3934
Market research	42292	0.0238	0.1526
Accountancy	42292	0.0794	0.2704
Access to finance	42292	0.2469	0.4312
Environment	42292	0.0170	0.1295
Main custom Foreign	42292	0.0055	0.0744
Craft certification	42292	0.2949	0.4560

Own Local	42292	0.4768	0.4994
Mother company	42292	0.0342	0.1819
Male manager	42292	0.7422	0.4373
Log workers	42292	0.7496	0.8394
(Log workers)^2	42292	1.2666	3.2160
Log Age	42292	1.7227	1.0917
(Log Age)^2	42292	4.1600	3.9232
Log labour Producti.	41665	8.8584	1.0648
Coob-Douglas TFP	41665	3.2308	0.7550
Translog TFP	41665	5.1407	1.0263
Log capital	41647	8.1121	1.7503
Log capital/worker	41665	7.3610	1.4038
Log materials	41647	8.5995	1.6346
Log materials/worker	41665	7.8484	1.2371
Markup	41647	2.2241	13.7252

Chapter 3 Innovation and employment growth in Ecuadorian firms

3.1 Introduction and literature review

The main objective of the chapter is to study the effects of innovation on firms' employment creation, acknowledging the potential heterogeneous effects of different types of innovations. In particular, by following the classification in the third edition of the Oslo Manual (OECD, 2005), we consider four types of innovations: product innovations, process innovations, organizational innovations and marketing innovations. The approach followed in the chapter is based on the model by Harrison *et al.* (2014), which was focused on the two types of innovation (product and process) that were considered in previous editions of the Oslo Manual (see, for instance, the second edition: OECD, 1997). Some of the ideas in this model were already present in Jaumandreu (2003), García *et al.* (2004), Harrison *et al.* (2008), Hall *et al.* (2008) and Peters (2008). This approach represents an advance in previous literature focused on the relationship between innovation and employment.[18] The reason is that it allows disentangling efficiency and demand effects of innovation when we have in our data sets information on sales due to new products. It was also specially meant for exploiting the information contained in innovation survey data sources.

To deal with the main objective in the chapter we use data coming from the Ecuadorian National Innovation Activities Survey 2013 (NIAS). This is a survey

[18] Pianta (2005) makes a detailed review of different types of studies of innovation and its relationship with employment at the macroeconomic and microeconomic level. He discusses different views in the literature about technological change and its effects. For example, some classical theories are focused on the labor savings effect of technological change. The main idea behind is that when firms introduce new machinery or new processes, in some cases, they require less number of workers.

sponsored by the Ecuadorian National Statistics and Census Office (INEC) and the Secretary of Superior Education, Science, Technology and Innovation (SENESCYT). It is the first time that in Ecuador has been made a survey about innovation decisions and performance at the firm level. The information in the survey corresponds to a three years' period and it is quite similar in structure and variables to the Community Innovation Surveys (CIS) for European countries.

The core idea incorporated in the approach by Harrison *et al.* (2014), although they only consider process and product innovations, is that the effects of innovations on employment act through two general channels: a direct and an indirect one. Hence, extending this idea to our wider group of innovation types, on the one side, process, organizational and marketing innovations might have a direct effect on employment that is expected to be negative if we anticipate a replacement of labor by machines and the reorganization of work and business practices, or if the introduction of marketing innovations has any effect in increasing production efficiency. This is known as the *displacement effect* of labor. But, additionally, there can also exist an indirect effect of process, organizational and marketing innovations (which may compensate the previous one) that consists on the creation of employment if firms increase sales due to the fact that more efficient firms could decrease prices and, hence, increase demand. This is known as the *compensation effect* on labor. On the other side, product and marketing innovations might have a direct effect on employment by the generation of new demand for the firm's products (*compensation effect*). But there could be also an indirect effect on employment in the opposite direction likely provoked, for instance, by a certain degree of product substitution of old products by new ones that, if produced more efficiently, require less labor (*displacement effect*).

Most of the evidence about the effects of innovation on employment are from developed countries and, furthermore, only about the two types of innovations considered in editions of the Oslo Manual previous to the one of 2005 (that is product and process innovations). Vivarelli (2014) has a survey of studies about the empirical relationship between firms' innovation activities and employment. He reveals that results may differ between countries but that there is evidence about a positive relationship between product innovation and employment, especially in high-tech sectors. We revise briefly in what follows some evidence found in papers that apply the approach in Harrison *et al.* (2014) for developed countries. Thus, for instance, Hall *et al.* (2008) find no displacement effect of labor from process innovation and a mild positive effect on labor for product innovation in Italian firms. Dachs and Peters (2014) for 16 European countries find that process innovation contributes to saving jobs. Damijan *et al.* (2014) for 23 European countries find that product, organizational and marketing innovations have a positive effect on employment, while process innovation has no effect. This final paper extends the more traditional analysis by incorporating non-technological innovations as a joint dummy variable for the performance of organizational or marketing innovations. However, it is interesting to notice that our work is the first one that considers marketing as a different innovation type to be considered separately in the context of the Harrison *et al.* (2014) model.

The model by Harrison *et al.* (2014) has also been used as the basic framework in some studies for Latin American countries (see Appendix C3. 1). In this group of papers we have the ones by Benavente and Lauterbach (2008) and Álvarez *et al.* (2011) for Chile, Aboal *et al.* (2015) for Uruguay, Monge-González *et al.* (2011) for Costa Rica, Crespi and Tacsir (2012) for four Latin American countries (Chile, Uruguay, Costa Rica and Argentina), and de Ejalde *et al.* (2011, 2015) for Argentina. They find in general a positive effect over employment for product innovation, but a non-clear cut for process innovation.

A recent paper for low and middle income countries in Africa, South Asia, Middle East and North-Africa and Eastern Europe and Central Asia is the one by Cirera and Sabetti (2016). They obtain a positive effect of product innovation on employment but no effects for either process or organizational innovations (this paper extends the analysis by also including this type of non-technological innovation).

In addition to the core objective of the chapter, we also have some supplementary goals. In this sense, we also are interested in providing some evidence about the link between different types of innovations and the composition of the firm's labor force in terms of skills and wages. We can consider both higher skills and wages as indicators of higher quality labor being required and created by more innovative firms. If this was the case, not only innovation is socially and economically desirable because it generates employment growth but also because it might help improving jobs quality by affecting skill composition of labor and wages (technology based wage premia). For instance, product innovation may increase variety and quality and, hence, may lead to skill upgrading and to higher wages.

In this line of research, some studies have found for European countries that organizational innovation is more relevant than product and process innovation for skill upgrading (see, for instance, Caroli and Van Reenen, 2001, Piva and Vivarelli, 2002, Piva *et al.*, 2005, and Greenan, 2003, for France and the UK, Italy, and France, respectively).[19] All this debate is related to the idea of a skill biased nature of technological change. About this particular issue, we find the works by Acs and Audretsch (1988), Acemoglu (1998), Giuri *et al.* (2008), Bogliacino and Lucchese (2016), and Marouani and Nilsson (2016), among others.[20] The common thought behind these works is that when firms introduce a technological change they create an "attraction" effect over the most qualified workers, since some tasks are replaced by another's that require more qualified labor.[21] In addition, it is also argued that skills improvement could increase the "distance", in terms of wages, between different types of workers. However, there is more empirical consensus about technology pushing and requiring superior skills than about generating polarization of wages.[22] In any case, our interest in this chapter about wages is about the effects of different types of innovations on absolute value of wages. Addressing the topic of a potential polarization of wages between different types of workers due to innovation is out of the scope of this chapter. Data limitations prevent us from pursuing this question.

Again, although there are several studies about technological change and skill bias in developed countries, they are scarce in developing countries. One exception is

[19] For 28 European countries, Damijan *et al.* (2014) study the impact of innovation on skill upgrading and obtain that product, process, and organizational or marketing innovation increase the demand for skilled labor.

[20] Vivarelli (2014) has a survey of studies about the empirical relationship between firms' innovation activities and labor skills. He reveals that results may differ between countries but there is evidence about a positive link between innovation and skills in OECD countries.

[21] According to Vivarelli (2013), firms' technological changes generate pressure over other production factors (including here human capital).

[22] For Autor and Dorn (2013) automating tasks is one of the relevant factors explaining polarization of skills and wages in the US.

the work by de Ejalde *et al.* (2015) for Argentina, in which they obtain that product innovation is skilled biased and process innovation has not effects on skills.

It is very much interesting for a middle income developing country like Ecuador, not only addressing whether different types of innovations contribute to the generation of employment but also whether the different types of innovations are associated with higher quality jobs in dimensions such as skills and wages.

Latin American Countries (LAC's) in general are not a region with a *"long tradition"* on innovative activities. In this direction, Lederman *et al.* (2013) show that LAC's have less product innovation than European or North American countries.[23] This is reinforced by the information according to the Global Innovation Index (GII) 2011 that reports a lag on innovation performance for LAC's.[24] Six European countries (Switzerland, Sweden, Finland, Denmark, Netherlands and United Kingdom), two North American (Canada and United States) and two Asian (Singapore and China/Hong Kong) appear as the leaders among 125 countries. In the group of LAC's, Chile was better located in a 38 position, while Ecuador was in the position 109.[25] For Ecuador in particular, Schwartz and Guaipatin (2014) highlight that the main drawbacks to explain why Ecuador lags behind other comparable countries are the insufficient R&D investment by the private sector, frictions from labor regulation, and deficiencies in

[23] They use information from the World Bank Enterprise Survey 2006-2010.

[24] The GII is a report with information about innovation performance at aggregate level for countries. More specifically, the GII incorporates information about inputs and outputs of the innovation process, and it takes also into consideration questions related with institutions, human capital, infrastructure, market sophistication, business sophistication, scientific outputs and creative outputs. See WIPO and INSEAD (2011) for methodological details and a complete ranking of countries.

[25] In the 2009 and 2010 GII, Ecuador was ranked 109 and 126, respectively.

education. However, as shown in Table C3.1, looking at global investments in R&D without distinguishing between public or private investments, Ecuador has the higher R&D expenditure as percentage of GDP among the group of Andean Countries (Colombia, Peru, Bolivia and Ecuador) but not when compared with other LAC's (such as Argentina, Brazil, Chile, Costa Rica and Mexico).[26] Something similar happens with other aggregates measuring other innovation input variables.

If we look at innovation output aggregates, one measure is the number of patent applications at country level. According to this indicator, Ecuador has only 10 patent applications in the period 2009 to 2011. This situates Ecuador, in terms of innovation, at large distance from the top LAC's and also from other developing countries.

[26] For example, Ecuador had 0.40% of R&D expenditure over GDP in 2010 that was greater than for other Andean Countries but, however, among other LAC´s for the period 2009 to 2011, only Chile had smaller values.

Table C3. 1 Some aggregated innovation and employment indicators.

Panel A: Andean Countries

Indicators	Bolivia			Colombia			Ecuador			Peru		
	2009	2010	2011	2009	2010	2011	2009	2010	2011	2009	2010	2011
R&D expenditure (% of GDP)	0.16	n/a	n/a	0.21	0.21	0.22	0.39	0.40	0.34	0.16*	n/a	n/a
Researchers in R&D (per million people)	145.71	165.95	n/a	165.13	184.88	160.66	118.35	141.30	180.30	n/a	n/a	n/a
Charges for the use of intellectual property, payments (in million US$)	18.00	19.00	20.00	298.00	362.00	424.00	47.00	54.00	65.00	152.00	196.00	215.00
Charges for the use of intellectual property, receipts (in million US$)	2.50	2.80	7.10	39.00	56.00	59.00	n/a	n/a	n/a	2.10	3.00	5.30
Patent applications, nonresidents	n/a	n/a	n/a	1,551	1,739	1,770	668	690	n/a	657	261	1,129
Patent applications, residents	n/a	n/a	n/a	128	133	183	6	4	n/a	37	39	39
Unemployment, total (% of total labor force)	3.40	n/a	2.70	11.80	12.00	11.10	6.50	5.00	4.20	4.40	4.00	3.90
Part time employment, total (% of total employment)	23.30	n/a	n/a	15.10	16.30	16.90	20.40	17.90	17.00	18.80	20.50	19.40
Vulnerable employment, total (% of total employment)	54.90	n/a	54.30	47.30	48.60	48.80	42.50	41.80	43.90	48.00	47.70	47.80

Source: World Bank Indicators.
* The last information for Peru on R&D expenditure over GDP is from 2004.

Table C3. 1 Some aggregated innovation and employment indicators.

Panel B: Other Latin American Countries

Indicators	Argentina			Brazil			Chile			Costa Rica			Mexico		
	2009	2010	2011	2009	2010	2011	2009	2010	2011	2009	2010	2011	2009	2010	2011
R&D expenditure (% of GDP)	0.48	0.49	0.52	1.12	1.16	1.14	0.35	0.33	0.35	0.54	0.48	0.47	0.43	0.45	0.42
Researchers in R&D (per million people)	1,071.53	1,154.21	1,208.48	656.34	698.10	n/a	288.71	319.72	353.37	997.94	1,232.71	1,327.47	367.87	379.75	383.21
Charges for the use of intellectual property, payments (in million US$)	1,461.00	1,618.00	1,958.00	2,512.00	3,225.00	3,747.00	596.00	726.00	773.00	64.00	63.00	214.00	1,823.00	658.00	774.00
Charges for the use of intellectual property, receipts (in million US$)	101.00	147.00	177.00	433.00	189.00	300.00	59.00	64.00	75.00	0.58	7.50	n/a	94.00	88.00	96.00
Patent applications, nonresidents	4,336	4,165	4,133	18,135	20,771	23,954	1,374	748	2,453	n/a	1,212	630	13,459	13,625	12,990
Patent applications, residents	640	552	688	4,271	4,228	4,695	343	328	339	n/a	8	14	822	951	1,065
Unemployment, total (% of total labor force)	8.60	7.70	7.20	8.30	n/a	6.70	9.70	8.10	7.10	7.80	7.30	7.70	5.20	5.20	5.20
Part time employment, total (% of total employment)	24.00	20.50	19.90	17.80	n/a	16.00	10.10	18.00	17.20	14.20	15.30	12.00	17.80	18.70	18.00
Vulnerable employment, total (% of total employment)	19.60	19.00	18.60	25.10	n/a	24.50	n/a	n/a	n/a	20.10	20.40	20.20	n/a	n/a	n/a

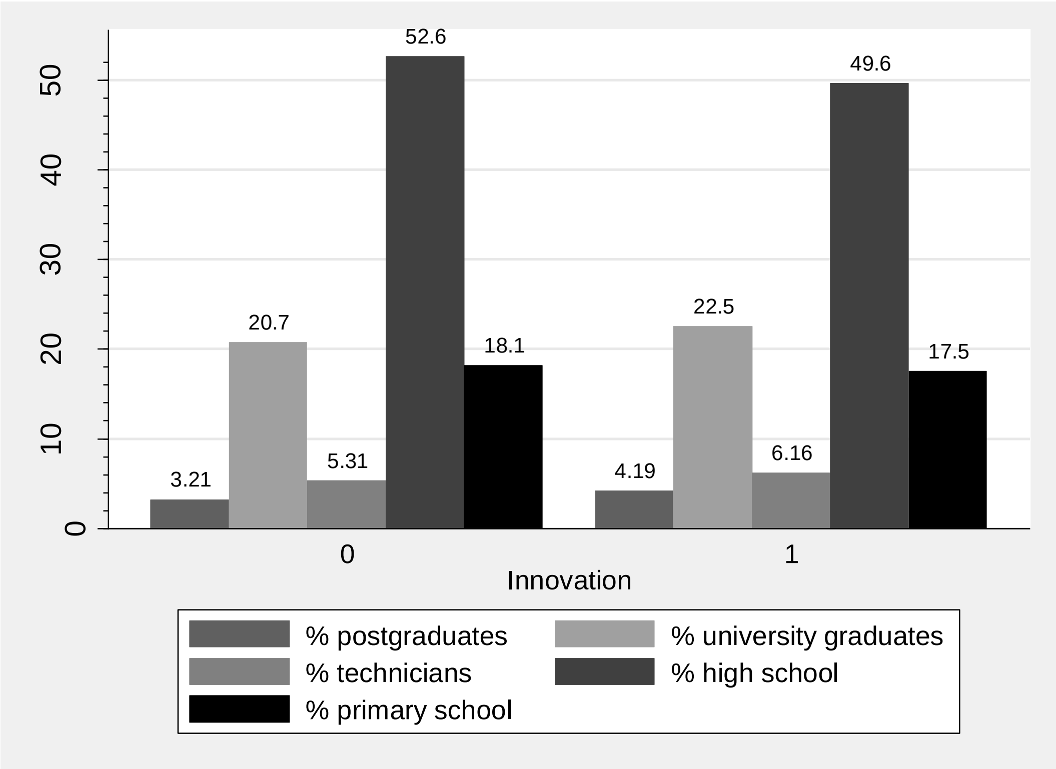
Source: World Bank Indicators.

In addition, paying attention now to some aggregated characteristics of the labor market in Ecuador, as shown in Table C3.1 Ecuador does not have a high unemployment rate. However, what is considered vulnerable employment is, on average, 42.73% of total employment. Employment vulnerability is an indicator to measure the quality of jobs. This indicator was established by the United Nations in their Millennium Goals for 2015. The way to obtain this indicator corresponds to the sum of own-account and contributing family workers over total employment.[27] That means that a large number of workers have "bad quality" jobs in Ecuador. It does look reasonable to think that innovation might have effects also on the quality dimension of jobs creation. A first piece of evidence in this direction comes from a descriptive analysis of data from the last Ecuadorian Economic Census (2010), covering the universe of firms. According to the information in the census, firms performing R&D activities (the only proxy in the census for the firms' innovative activity) pay higher wages than firms without R&D activities.[28] A second piece of descriptive evidence is presented in Figure C3. 1, which shows the distribution of workers in firms by education level. In Ecuadorian innovative firms there is a higher proportion of workers with higher level of education. The data displayed in the figure comes from the main dataset in this chapter, the Ecuadorian National Innovation Activities Survey 2013 (NIAS). Hence, innovative firms are the ones that perform any of the four innovative activities considered in this chapter: product, process, organizational or marketing innovations.

[27] For more information, see International Labour Office (2009).

[28] This result is obtained by performing a mean test of wages between innovative and non-innovative firms. The null of equal wages is rejected (at 1% level) in favor of innovative firms. The difference in log wages is 1.668.

Figure C3. 1 Distribution of workers' education by firm innovative status



In summary, we contribute to the related literature is several aspects. First, we add the unexplored case of Ecuador to the existent literature on this topic for some Latin American countries. Second, as previous works have not generally included among innovations either organizational and/or marketing innovations, we enlarge the focus of our study by including these categories of innovation jointly with the more traditional technological innovations (product and process). Third, we are not only focused on the jobs creation dimension of innovation but also in the quality of these jobs. In this direction, we explore the relationship between different firms' innovation types and jobs quality dimensions such as skills composition and average wages per employee.

The obtained results in the chapter are manifold as regards the effects of different types of innovations on firms' employment growth. First, process innovation increases production efficiency over time justifying a decrease in firms' labor (*displacement effect*). However, the estimated effect for organizational innovation, although with a negative sign over employment growth, is statistically non-significant. Second, growth in sales due to new products generates a *gross* increase in firms' labor because efficiency in the production of old products is higher than in the production of new ones (the opposite of a *displacement effect*). Furthermore, the *net* effect of product innovation on employment growth is still positive, large and highly significant, although smaller than the *gross* effect. This is due to a certain degree of cannibalization of old products by new ones in product innovative firms, which suffer from a decrease in demand for old products. Third, we find evidence about marketing innovation also increasing employment growth by very likely increasing firms' profits through the increase in prices of new products as regards old ones. Fourth, non-product innovators enjoy a growth in sales of already existing products that causes employment growth (this evidence goes against a business stealing effect from product innovators). Finally, overall, the positive effects of innovation on employment (from product and marketing innovations) surpass the negative ones (from process innovation, and from some cannibalization of old products by new ones inside product innovative firms).

As regards the two considered quality dimensions of the employment growth generated by innovations, skill composition and wages, we obtain that innovative employment growth positively correlates with a superior skill composition of the firm's labor force and that this is mainly driven by a positive effect on skills composition associated to sales growth due to new products. The opposite effect is found for process innovation and non-significant effects are found for marketing and organizational innovations. In addition, results also indicate that being an innovative firm is positively related with higher wages per employee.

Therefore, innovation not only has *net* employment effects in the economy, but we also find some evidence in favor of innovative activities by firms also positively influencing the quality of generated jobs in terms of skills and wages.

There are some interesting policy implications from our results. One of them is that for Ecuador both product and marketing innovations are relevant tools to increase employment in the short and medium run. Another one is that also product innovation seems to be a type of innovation positively associated with skills, highlighting the relevance of this type of innovation for promoting the demand of human capital in developing countries. Product innovation in Ecuadorian firms might be associated to a more complex innovation than process innovation, requiring in this case more qualified workers. Finally, in general, innovative firms display higher average wages per employee.

The chapter is organized as follows. Section 3.2 defines the four types of innovations we consider in this chapter. Section 3.3 explains the theoretical background and the empirical model. Section 3.4 presents the main data source employed in the chapter and some descriptive statistics. Section 3.5 presents and discusses obtained results. Finally, section 6 concludes.

3.2 Types of innovation

The Oslo Manual (2005), developed jointly by the European Commission (Eurostat) and the OECD, provides guidelines for collecting and interpreting innovation data in an internationally comparable manner. In this version of the manual innovation is classified in four types: product, process, organizational and marketing innovations. In previous versions of the manual there were only considered as innovations product and process innovations, reason for which there are many previous studies than when analyzing innovation only consider these two types. Traditionally, product and process innovations are named as *"technological innovations"*. Hence, for instance, Utterback and Abernathy (1975) defined firms' product innovation as the introduction of a technology improvement with commercial or market interest. In the same line, the Oslo Manual (OECD, 2005) defines it as: *"is the introduction of a good or service that is new or significantly improved with respect to its characteristics or intended uses. This includes significant improvements in technical specifications, components and materials, incorporated software, user friendliness or other functional characteristics*" (OECD and Eurostat, 2005 p. 48). Similarly, process innovation is also traditionally considered a "technological innovation", since firms interested in maximizing their benefits have another way to do it by the development and implementation of new technology in production. For example, Barras (1986) differentiates product and process innovation explaining that the first is related to what the firm offers to the customer, while the second is related to the mode of production. The definition of process innovation according to the Oslo Manual (OECD, 2005) is: *"the implementation of a new or significantly improved production or delivery method. This includes significant changes in techniques, equipment and/or software"* (OECD and Eurostat, 2005 p. 49). As can be seen, both types of innovations are related to the production side of the firm. On the one hand, product innovations modify the firms' output directly. In this case, the aims of firms could be: 1) sell new products to the same market, 2) sell new products to a new market, 3) change its products for sale at the same market or, 4) change its products for sale to the new market. On the other hand, firms introducing process innovations could have mainly two aims. First, the firm could enjoy cost savings when it changes its production process and, second, it might increase its productivity as a result.

Certainly, the Oslo Manual (OECD, 2005) has maintained the largest possible degree of continuity with the previous definition of technological product and process innovation used in the second edition of the Manual. However, marketing innovations and organizational innovations widen the kind of innovations covered by the Manual as compared to previous versions. For this reason, they are more recently treated in the economic literature and, many times, even with a management perspective. As examples of works incorporating any of these two types of innovations in a variety of contexts, Rust *et al.* (2004) explain marketing innovation in terms of strategies over product, price and promotion. Additionally, Murphy (2002) classifies an organizational innovation in three types: management, production approaches and external relations. The OCDE and the European Commission include both types of innovations at the same level than product and process innovations in the Oslo Manual (OECD, 2005). Marketing innovation is defined as "*the implementation of a new marketing method involving significant changes in product design or packaging, product placement, product promotion or pricing*" (OECD and Eurostat, 2005 p. 49). In the economic literature, there is not a large evidence about marketing innovation affecting firms' output. However, Junge *et al.* (2016), using information about marketing innovations in their study for productivity with Danish firms, found a positive effect on firms growth. Also, they concluded that when firms introduce marketing innovations and product innovations, their growth is faster than when they take only one of these decisions. Finally, organizational innovation *"is the implementation of a new organizational method in the firm's business practices, workplace organization or external relations"* (OECD and Eurostat, 2005 p. 51). There are some econometric studies that jointly take into account marketing and organizational innovations. For instance, Flikkeman *et al.* (2007) and Mothe and Nguyen-Thi (2012) include both of them and call them *"non-*

technological" innovations. Also Schubert (2010) includes them as regressors in a study to determine the relationship with market structure and some other firms' characteristics.

The Oslo Manual (OECD, 2005) also highlights the main distinguishing factors between product and marketing innovations, or between process and organizational innovations. Accordingly, if there is a significant change in the product's functions or uses, it should be called product innovation. However, when the innovation relates to the firms' sales/marketing methods, it should be called marketing innovation. Of course, some innovations may combine both product and marketing innovations. As regards the distinction between process and organizational innovations, the former deals primarily with the implementation of new equipment, software and specific techniques or procedures, while the latter deals primarily with people and the organization of work (OECD and Eurostat, 2005, p. 55). Again, the two innovations may come together in some cases.

3.3 Theoretical background and empirical model

We rely on the structural model developed by Harrison *et al.* (2014) to disentangle the effects of product and process innovations on firms' employment growth. In the following we describe this model, although at a certain point it will be incorporated the extension to take into account organizational innovations in the empirics. This extension of the model can be already found in Peters *et al.* (2013), Damijan *et al.* (2014), Cirera and Sabetti (2016) and Dachs *et al.* (2017).[29] Lastly, although there is not a corresponding theoretical model explicitly incorporating marketing innovations, we will justify the inclusion of them in our empirical specification. As far as we know, the only paper that incorporates marketing innovations into this framework is Damijan *et al.* (2014), but they consider marketing innovations jointly with organizational innovations, while we argue that these two types of named non-technological innovations should be treated separately.[30]

3.3.1 Theoretical background

The Harrison et al. (2014) model considers two periods and two goods. The two periods are $t=1$ and $t=2$. The two goods are old products ($j=1$) and new products ($j=2$). Production in $t=1$ is only about old products (i.e., $Y_{jt}=Y_{11}$). Differently, in $t=2$ the firm produces a mixture of old and new products (hence, $Y_{j2}= Y_{12}+ Y_{22}$, with $Y_{j2}>0$, $Y_{12}\geq 0$ and $Y_{22}\geq 0$). Product innovation can be zero, in which case in period 2 the firm only produces old products, or it can be positive, in which case the firm will be in a range of output between an effective mixture of old and new products and the extreme case of only producing new products. This will depend on the degree of complementarity or substitutability between the two types of products.

[29] Evangelista and Vezzani (2012) also study the impact of product, process and organizational innovations on employment but with a different methodology. They perform their analysis for European countries and find that organizational innovation has a positive effect on employment.

[30] Employing a different approach, Falk (2015) added to technological innovations also organizational and marketing innovations in a study with Austrian data. However, he obtains that both non-technological innovations do not have an effect on employment, while process has a negative effect and product a positive one.

They further assume specific production functions for the production of old products in period 1, the production of old products in period 2 and the production of new products in period 2, respectively, as follows:

$$(1)\quad \begin{aligned} Y_{11i} &= \theta_{11}F(K_{11i},\ L_{11i},\ M_{11i})e^{\eta_i} \\ Y_{12i} &= \theta_{12}F(K_{12i},\ L_{12i},\ M_{12i})e^{\eta_i - u_i} \\ Y_{22i} &= \theta_{22}F(K_{22i},\ L_{22i},\ M_{22i})e^{\eta_i - v_i} \end{aligned}$$

where i indicates firm, θ_{jt} are productivity (efficiency) terms, η_i allows for firm's fixed effects in the production technology, and it is acknowledged the potential existence of unanticipated productivity shocks (u_i and v_i, respectively) in the production of both types of products in period 2. The firm can vary production efficiency of old products (θ_{1t}) by implementing, for instance, process innovations between periods 1 and 2. However, as by construction new products are not produced at period 1, this type of innovations cannot improve production efficiency of new products, but only of old products from period 1 (θ_{11}) to period 2 (θ_{12}). Of course, the model does not deny that there can be non-innovation-related factors which may also affect efficiency in the production of old products from one period to the next.

In this setting (for more details see Harrison *et al.*, 2008, 2014), cost minimizer firms have the following relative demands of labor input:

$$(2)\quad \begin{aligned} \frac{L_{12i}}{L_{11i}} &= \frac{\theta_{11}}{\theta_{12}} \cdot \frac{Y_{12i}}{Y_{11i}} \cdot e^{u_i} \\ \frac{L_{22i}}{L_{11i}} &= \frac{\theta_{11}}{\theta_{22}} \cdot \frac{Y_{22i}}{Y_{11i}} \cdot e^{v_i} \end{aligned}$$

where the first line corresponds to the demand of labor for the production of old products in period 2 over the one in period 1 and, the second line, to the demand of labor for the production of new products in period 2 over the demand of labor for the production of old products in period 1. Notice that already in (2), but also in the subsequent model equations, firms' individual effects η_i have been differentiated out. This is relevant for estimation since we do not have to worry about potential endogeneity issues coming from correlation of them with explanatory variables in the regressions.

Next, they decompose employment growth from period 1 to period 2 in employment growth for old and new products as follows

$$(3) \quad \frac{\Delta L_i}{L_i} = \frac{(L_{12i}+L_{22i})-L_{11i}}{L_{11i}} = \frac{L_{12i}-L_{11i}}{L_{11i}} + \frac{L_{22i}}{L_{11i}} \simeq \ln\left(\frac{L_{12i}}{L_{12i}}\right) + \frac{L_{22i}}{L_{11i}}$$

and derive the following employment growth equation by combining (2) and (3):

$$(4) \quad \frac{\Delta L_i}{L_i} = -\left(\ln\theta_{12} - \ln\theta_{11}\right) + \left(\ln Y_{12i} - \ln Y_{11i}\right) + \frac{\theta_{11}}{\theta_{22}} \cdot \frac{\bar{Y}_{22i}}{Y_{11i}} + u_i$$

where $\bar{Y}_{22i} = Y_{22i} \cdot e^{v_i}$ is the production of new products eliminating the unanticipated productivity shock v_i.

According to (4), the firm can generate employment through four channels (we follow the order of terms in the right hand side of this expression): i) the decrease in efficiency (productivity) in the production of old products over time (first term, $\theta_{12} < \theta_{11}$); ii) the increase over time in the demand for old products (assuming production follows demand, this is the second term in (4)); iii) the increase in demand (production) due to new products (that were non-existent in period 1, but exist in period 2, third term in (4)); and, iv) the materialization of a positive unanticipated productivity shock affecting production of old products in period 2 (the final term u_i).

3.3.2 Empirical model

To obtain an empirical version of expression (4) Harrison *et al.* (2014) define the following terms. Let $l_i = \Delta L_i / L_i$; $\alpha = -\left(\ln\theta_{12} - \ln\theta_{11}\right)$; $y_{1i} = \left(\ln Y_{12i} - \ln Y_{11i}\right)$; $y_{2i} = \overline{Y}_{22i} / Y_{11i}$; and, $\beta = \theta_{11} / \theta_{22}$. Then, substituting them in (4) and moving the (demand) production growth rate for old products y_{1i} to the left hand side, they get the following expression:[31]

(5) $l_i - y_{1i} = \alpha + \beta \cdot y_{2i} + u_i$

In this expression, they subtract from α the change in efficiency in the production of old products due to process innovations. The next extension of the empirical model in Harrison *et al.* (2008, 2014) is found in Peters *et al.* (2013), Cirera and Sabetti (2016) and Dachs *et al.* (2017). All of them treat and consider organizational innovations similarly to process innovations and, thus, also subtract from α their role in changing efficiency over time in the production of old products. After both

[31] Notice that by construction the coefficient of y_{1i} is equal to one and it is subtracted from the employment growth l_i .

subtractions, what remains as a constant term in the model is a new term α_0 that captures the change in efficiency in the production of old products due to non-firm specific innovation-related factors:

(6) $l_i - y_{1i} = \alpha_0 + \alpha_1 \cdot Process_i + \alpha_2 \cdot Organizational_i + \beta \cdot y_{2i} + u_i$

In (6), if we consistently estimate the parameters α_0, α_1 and α_2, we can differentiate in firms' employment growth the effects of changes over time in efficiency (productivity) in the production of old products: unrelated to the firm innovation activities (α_0), related to process innovation (α_1), and related to organizational innovation (α_2). All these effects of changes in efficiency in the production of old products are isolated ceteris paribus the growth rate for old products (y_{1i}). In (6), α_0 is expected to be negative as far as there is a systematic increase over time in the efficiency of production of old products. This will decrease employment requirements. It represents the minus efficiency growth producing old products for non-innovators. On the other hand, consistently estimating β we get an estimate of the relative efficiency in the initial production of old products and that of new products (θ_{11}/θ_{22}). This parameter shows the effect of the growth in demand (production) due to new products (relative to old products Y_{11i}; notice that $y_{2i} = \bar{Y}_{22i}/Y_{11i}$ can be written as $y_{2i} = \left(\bar{Y}_{22i} - 0\right)/Y_{11i}$ since in period 1 there are not new products) on firms' employment growth.[32] The structure incorporated in the underlying theoretical model that we use as the background for our empirical model implies that if new products are relatively more efficiently produced than old products initially, that is $\theta_{22} > \theta_{11}$ (and, hence,

[32] Since new products are not produced at period 1, we do not measure the real output growth of new products but the real output growth rate *due* to new products.

$\left(\theta_{11}/\theta_{22}\right)<1$), the extra production that new products generate ($\bar{Y}_{22i}$) will cause an employment growth lower than the one that would have been generated by the same increment in production of old products (keeping constant for them its production efficiency in period 1, i.e., θ_{11}). The contrary would happen when new products are produced relatively less efficiently than old products. In this case, $\theta_{22}<\theta_{11}$ and, hence, $\left(\theta_{11}/\theta_{22}\right)>1$, implying that the extra production due to new products increases labor more than what would have been the increase in case of the same increment in the production of old products (again, keeping for them constant its efficiency of production in period 1).

Lastly, if we consider the way in which Damijan *et al.* (2014), the only paper including marketing innovations into this framework (as far as we know), incorporates marketing innovations, expression (6) is modified as follows:

(7) $l_i - y_{1i} = \alpha_0 + \alpha_1 \cdot Process_i + \alpha_2 \cdot Organizational_i /Marketing_i + \beta \cdot y_{2i} + u_i$

where a joint dummy about the firm's performance of organizational or marketing innovations is intended to capture how any of them affects (in the same way) the relative efficiency (from the initial period to the final one) in the production of old products.

What we claim in this chapter is that at the minimum the two types of termed non-technological innovations should be treated separately. Hence, the empirical model estimated in this chapter will be:

(8) $l_i - y_{1i} = \alpha_0 + \alpha_1 \cdot Process_i + \alpha_2 \cdot Organizational_i + \alpha_3 \cdot Marketing_i + \beta \cdot y_{2i} + u_i$

Notice that with estimation of α_1 and α_2 we identify the direct (*gross*) effects that process and organizational innovations might have on employment, which are expected to be negative when there is replacement of labor by machines and the reorganization of work and business practices (we then identify the *displacement effects* of labor due to the increase in efficiency over time in the production of old products that implies less labor per unit of output).[33] The indirect effects of process and organizational innovations (which are the *compensation effects*) that consist on the creation of employment if firms increase sales due to the fact that more efficient firms could decrease prices and, hence, increase demand, are not identified by any estimated model coefficient. However, it will be possible to say something more about the effects of process and organizational innovations in the section bellow where we perform a decomposition analyses for labor growth in its different components.

In addition, what we identify when estimating β in the model is the indirect (*gross*) effect of product innovation on employment provoked, for instance, by a certain degree of product substitution of old products by new ones that when produced more efficiently, require less labor (*displacement effect* in this case, the opposite will happen when produced less efficiently).[34] However, the direct effect of product innovation on employment through the generation of new demand for the firm's new products (*compensation effect* of the previous displacement effect) is not identified by the model

[33] They are *gross* effects since they identify effects on labor demand from changes in efficiency in the production of old products due to process or organizational innovations holding firms' output fixed.

[34] Again, it is a *gross* effect since it identifies the effect on labor demand from a difference in relative efficiency in the production of old products with respect to new products, not considering changes in firms' output and in firms' output distribution over time between old and new products.

parameters. However, it will be possible to say something more about the effect of product innovation in the section bellow with the decomposition analysis.

Before discussing what the estimated model identifies with the coefficient α_3, there are still two empirical questions to go through. The first one is that (8) is not yet our estimation equation. The reason is that in (8) growth rates of sales for old products and due to new products should be in real terms. Hence, for empirical purposes we need price deflators. Thus, as standard in this literature, since there is not survey information on firm-level prices, it is considered the use of industry-level prices instead for obtaining the real growth rate in sales coming from old products. In particular, the growth rate for prices of old products is proxy by the price growth rate at the 3–digit *s* industry level (based on the *ISIC Rev.4* classification). The level of disaggregation for manufacturing is 3-digits. Therefore, in (8) we substitute y_{1i} by its estimate in real terms g_{1i}. Differently, we cannot have an estimate for the real growth rate of sales due to new products and, then, we just plug its nominal growth rate. This implies substituting y_{2i} in (8) by its observed value $g_{2i} = (1+\pi_{2i})y_{2i}$, where π_{2i} is the difference in prices of new products in period 2 and old products in period 1 over the price of old products in period 1. This prices information is not even observed at the industry level.[35] Accordingly, our version for estimation of (8) becomes:

[35] The growth of old products taking account of prices in the two different time periods involved could be defined as: $\frac{P_{12}Y_{12}-P_{11}Y_{11}}{P_{11}Y_{11}}$, where the price difference is $\pi_1 = \frac{P_{12}-P_{11}}{P_{11}}$. Our proxy for it is taken at the industry level from country statistics. In the case of new products this is not possible. If we define that the nominal growth rate of production due to new products is: $g_2 = \frac{P_{22}Y_{22}}{P_{11}Y_{11}}$, to get the corresponding real growth rate we would require the information on prices for old products in period 1 and that of new

(9) $l_i - g_{1i} = \alpha_0 + \alpha_1 \cdot Process_i + \alpha_2 \cdot Organizational_i + \alpha_3 \cdot Marketing_i + \beta \cdot g_{2i} + \varepsilon_i$

where $\varepsilon_i = -\beta\pi_{2i}y_{2i} + u_i$. Equation (9) is a labor demand equation that is our estimation equation.

The second empirical question to go through requires discussing about some potential endogeneity issues in estimation of (9). Notice that already in (2) but also in the subsequent model equations firms' individual effects η_i have been differentiated out. This is relevant for estimation since we do not have to worry about potential endogeneity problems coming from correlation between individual effects and explanatory variables in the regressions. In principle, another possible issue could be simultaneity of investment decisions and the unanticipated productivity shock to the production of old products in period 2, u_i. But, however, the model assumes that previously to period 2, firms decide on their investments in R&D and other types of informal or non-technological innovation investments in order to obtain innovations. Hence, the model assumptions about the timing of investment decisions prevents u_i to be forecasted in advance.[36, 37]

Differently, in the application with real data of the model developed by Harrison et al. (2014) there is a real concern about a specific type of endogeneity problem. This is

products in period 2, something absent in any CIS type innovation survey that cannot be proxy by information at the industry level from country statistics.

[36] A similar timing for investment decisions is already incorporated in Olley and Pakes (1996), implying that current investment decisions depend on past productivity shocks.

[37] Harrison *et al.* (2008, 2014) note that there are good reasons to think that productivity shocks are not predictable by firms at the moment of deciding their technological investments.

the measurement error affecting the sales growth rate due to new products in g_{2i} in expression (9) above. As g_{2i} is the proxy for $y_{2i} = \bar{Y}_{22i} / Y_{11i}$, and we do not have in typical surveys information about the difference in prices of new products in period 2 and old products in period 1, it is clear that this information remains in the regressor g_{2i} (which is a nominal growth rate instead of a real one) and generates endogeneity with respect to the new error term in (9) because of the measurement error. The likely effect of the measurement error problem is an attenuation bias in the estimation of β in (9) by OLS.[38] The solution to this problem will be the use of instrumental variables correlated with g_{2i} but uncorrelated with the price differential component that would remain in the error term.

Whatever bias in the measurement of g_{2i} is corrected with suitable instruments. In particular, we will use four instruments. First, we use a variable from the survey that indicates the relevance that for the introduction of product innovations has the objective of increasing the range of products and services of the firm. A variable *increased range of products* is constructed with the five-level Likert scale question in the survey (with lower values indicating no relevance or low relevance, and the higher value indicating high relevance). Second, we construct a dummy variable with the question in the survey about how relevant is for the firm when performing product innovation, the information provided by customers and clients (variable *clients as information source*). The variable takes value 1 when this source of information has a high relevance for innovation and 0 otherwise. These two variables have also been used as instruments in Harrison *et al.*

[38] Notice that without correction for endogeneity the estimated coefficient will combine the relative efficiency in the production of old and new products and the unobserved information about relative prices for these two types of products.

(2008, 2014), Peters (2008), Peters *et al.* (2013) and Dachs and Peters (2014), and the first one in Jaumandreu (2003) and Dachs *et al.* (2017). Third, we consider the information in the survey about firms introducing product innovation even though their market was suffering from demand uncertainty or was dominated by more established firms. It could be the case that under this market situation the firm can obtain through product innovation a higher increase in sales due to the introduction of new products. The corresponding dummy variable is named *reaction to the market*. Finally, we introduce another dummy variable that measures the relevance of replacing outdated products as aim for product innovation. The dummy variable has a value of 1 if this is highly relevant for product innovation and 0 otherwise (this variable is named *replacement of outdated products*). Although instruments have been in principle selected on the basis of two criteria: 1) not being suspicious of generating a particular change in prices of new products as regards to old products (in other words, expected to be uncorrelated with the error term) and 2) being related to sales growth due to new products; their validity will be an empirical question formally tested in the results section.

Now, we can already discuss what the estimated model in (9) identifies with the coefficient α_3 associated to marketing innovation. Let us remember again the definition of marketing innovation in the Oslo Manual (OECD, 2005): "*the implementation of a new marketing method involving significant changes in product design or packaging, product placement, product promotion or pricing*". Accordingly, the Manual also highlights that in case of doubt it should be considered product innovation (and not marketing innovation) when there is a significant change in the product's functions or uses. Differently, when the innovation relates to the firms' sales/marketing methods, it should be considered a marketing innovation (and not a product innovation).

All the potential effects of marketing innovation on employment growth are more diverse and complex than for the previous types of innovations. First, we can think on a direct effect through the generation of new demand for the firm's products. Marketing enhances commercial success by increasing the awareness of potential customers.[39] In the model, there are old and new products being produced. Hence, in principle, marketing innovations may affect both growth in sales of old products and growth in sales due to new products. On the one side, we can consider that new marketing methods implemented between period 1 and period 2, very likely can affect the demand of old products in period 2 as regards to period 1, what is already incorporated into the growth rate for old products, g_{1i}. Hence, this effect is not identified by the model parameters. On the other side, we expect marketing innovations affecting new product sales to be already incorporated in the increase in production in period 2 due to new products, g_{2i}. This will be extra production in period 2 encouraged by marketing innovations affecting new products sales. Hence, this effect is also not identified by the model parameters since it is already incorporated in g_{2i}.

Under the scenario of marketing innovation affecting mostly what in the model are defined as old products (products already produced at period 1), what the model identifies by estimating coefficient α_3 is the existence of any effect of marketing innovation on employment growth acting through the channel of affecting efficiency in the production of old products over time (a similar effect captured by α_1 and α_2 for process and organizational innovation, respectively). This was the implicit assumption in Damijan *et al.* (2014), although they were further assuming that this efficiency effect

[39] Marketing innovation can have an effect on employment through firms' sales growth (Som *et al.*, 2012, and Evangelista and Vezzani, 2012).

of marketing innovation on employment was identical to the one for organizational innovation (as α_2 and α_3 in (9) were constrained to be equal in (7)). In this case, since it is expected marketing innovation to increase labor productivity, the anticipated sign for α_3 is negative.[40] This is a direct (gross) effect of marketing innovation that obeys to a *displacement effect* of labor due to the increase in efficiency over time in the production of old products. The inclusion of marketing innovation contributes to a better identification of α_1 and α_2 for process and organizational innovation, respectively. However, similarly to process and organizational innovations, there could also exist an indirect effect increasing employment if more efficient firms decrease prices and generate new demand for old products. This is a *compensation effect* not identified by any estimated model coefficient and already incorporated in g_{1i}. If this *compensation effect* exists, it would reinforce the generation of new demand for the firm's old products coming from the enhancement of commercial success due to marketing innovation increasing the awareness of potential customers.

[40] In Corrado *et al.* (2009) firm-specific investment in intangibles such as brand name (equity), from where investments on advertising are a large part, have a proportion that can be considered intangible capital and that contribute to the increase in labor productivity. They estimated that about 60 percent of total advertising expenditures had long-lasting effects (effects that last more than one year). Furthermore, Crass and Peters (2014) find that branding capital (measured by marketing expenditure and trademark stocks) has strong positive labor productivity effects. They use marketing expenditure as a proxy for reputation or branding capital. Their marketing expenditure includes advertising, conceptual design of marketing strategies, market and customer demand research and establishment of new distribution channels. Bontempi and Mairesse (2015) name advertising and trademarks "customer intangible capital" and consider it a productivity enhancing investment. We can interpret the performance of marketing activities in the three-year period *t-2* to *t* as an improvement in branding capital and reputation.

Under the scenario of marketing innovation affecting mostly what in the model are defined as new products (products produced and sold only at period 2), by estimating coefficient α_3 we take into account the existence of an omitted variable bias affecting the estimation of β that is corrected by including the marketing dummy. The omitted variable bias is likely to appear, for instance, if marketing activities are positively correlated with nominal growth in production due to new products ($g_{2i} = P_{22}\bar{Y}_{22i} / P_{11}Y_{11i}$; this implies in fact correlated with $P_{22}\bar{Y}_{22i}$, since $P_{11}Y_{11i}$ is a fixed value in period 1) and, simultaneously, both nominal growth in production due to new products (g_{2i}) and marketing innovation have a positive effect of its own on employment growth (that is $\beta > 0$ and $\alpha_3 > 0$). This positive effect of its own for marketing innovation may appear when it affects positively firms' profits (apart from a possible increase in real sales of new products) by increasing consumers' perceived quality of new products and reinforcing branding and consumers' loyalty. Through this channel, marketing innovation very likely increases relative prices of new as regards to old products (the later in period 1; notice that in the nominal growth rate of sales due to new products, g_{2i}, owing to lack of deflators, it remains the relative price P_{22}/P_{11}) and, hence, it increases profits, simultaneously increasing the value of our regressor g_{2i} in (9) and, then, contributing to the measurement error problem in this regressor. It is worth noting that this may also apply to old products, since reinforcing these type of intangible assets very likely benefits all firm's product lines. However, if it affects old product prices in period 2 with respect to period 1, this is not a problem since the increase in production from old products has been adjusted from nominal to real terms by using available deflators. If marketing innovation increases profits by increasing prices of new products, firms asymmetrically hit by the business cycle and/or financially constrained can alleviate internal funds limitations to labor force hiring. This type of described omitted variable bias will overestimate the coefficient $\beta = (\theta_{11}/\theta_{22})$, increasing the likelihood of concluding that production growth due to new products generates higher employment than would have generated a similar increase in production because of old products. Hence, under this scenario, controlling for marketing innovation contributes to the model estimates in three directions. First, α_3 captures things such as employment growth associated to a profits increase. Second, its inclusion contributes to solve a potential problem of overestimation bias in the model parameter β. That is to a better identification of the effect of the relative efficiency in the production of old products as regards to new ones in explaining employment growth generated by growth in sales due to new products. Third, by including marketing as a regressor in (9) we partly clean the error term in (9), $\varepsilon_i = -\beta\pi_{2i}y_{2i} + u_i$, from the part of the unobserved component of P_{22}/P_{11} (which is behind the unobserved deflator π_{2i}) that is explained by marketing innovation. Hence, the error term will be net of the unobserved price differential between new and old products prices generated specially by marketing innovation. This reduces the endogeneity component in ε_i. In any case, whatever endogeneity problem because of measurement error in g_{2i} is altogether solved by the instrumental variables approach previously presented.

If marketing innovation both affects old and new products, which effect dominates in α_3 is an empirical matter. This coefficient might reflect either the negative *displacement effect* over employment due to the increase in efficiency over time in the production of old products or the positive effect over employment for firms that are financially constrained and which are alleviated by an increase in profits coming from an improvement in perceived quality, reputation, branding and consumers loyalty (what increases relative prices for new products as regards the initial price for old products).

Summarizing, what the model and the data allow identifying from (9) in economic terms is the following: i) employment growth effects coming from a systematic (not coming from own firm innovation) change over time in the production efficiency of old products (α_0); ii) employment growth *gross* effects coming from an endogenized evolution of production efficiency over time of old products that has to do with the introduction of firms' process innovations (α_1) and organizational innovations (α_2); iii) employment growth *gross* effects due to the introduction of product innovations (β); and, iv) a mixture in α_3 of two *gross* effects on employment associated to marketing innovation: a negative one due to the increase in efficiency over time in the production of old products and a positive one for financially constrained firms that increase new product prices and, hence, profits, encouraging new hiring of workers. Which effect dominates is an empirical question.

3.4 Data and descriptives

The data used in this chapter is from the Ecuadorian National Innovation Activities Survey 2013 (NIAS) "*Encuesta Nacional de Actividades de Innovación 2013*". This is a survey sponsored by the Ecuadorian National Statistics and Census Office ("*Instituto Nacional de Estadísticas y Censos*", INEC), and the Secretary of Superior Education, Science, Technology and Innovation ("*Secretaría de Educación Superior, Ciencia, Tecnología e Innovación*", SENESCYT). It is the first time that in Ecuador has been made a survey about innovation decisions and performance at the firm level. In particular, the NIAS provides information about firms' characteristics related to innovation activities following the Frascati Manual and the Oslo Manual Guide of the OECD (OECD, 2002; OECD and Eurostat, 2005). Hence, it has information on the performance of product innovations, process innovations, organizational innovations and marketing innovations. The information in the survey corresponds to the period 2009-2011 and is similar in structure and variables than the Community Innovation Surveys (CIS) for European countries.[41] The NIAS also includes other firms' characteristics such as sector of activity, sales and employment. The survey covers 2,815 firms extracted from the population in the last Ecuadorian Economic Census (2010), covers all regions in the country and is representative of industry-size strata. In the survey, NIAS includes all type of sectors following the ISIC Rev. 4 classification from the United Nations, except agriculture. The survey also excludes firms with less than 10 employees. Answering the questionnaire is compulsory for firms. In our analysis in this chapter, we further exclude mining and quarrying, construction, and utilities (water supply and electricity, gas, steam and air conditioning supply). After this, we end up with 2,502 firms. Further cleansing the data from missing values in relevant variables for our analysis, we end up with an estimation sample of 2,437 firms.

Besides information about the performance of innovation activities as recognized by the Oslo Manual (OECD and Eurostat, 2005), some information very relevant for our analysis that is included in the NIAS, also present in CIS datasets, is about employment and firms' sales in 2009 and 2011. Furthermore, firms introducing new products also answer the question about the share (*S*) of sales during the period 2009-2011 that correspond to the introduction of new products (what in the model are called new products). The existent products at the beginning of 2009 is what the model

[41] Given the temporal length in the survey, 3 years, we will estimate in this chapter the short and medium-run effect of firms' innovation on employment.

calls old products. Indeed, information on sales for the initial and the final year covered by the survey plus information about the share of sales for new products, allows us calculating the sales growth due to new products, and by difference with the (nominal) total sales growth we obtain the nominal sales growth for old products.

In more detail, we can take directly from the survey the value of S (current sales new/(current sales new+current sales old)) and directly construct the nominal total sales growth $\hat{g}$ ((current sales old+current sales new-past sales old)/past sales old). From these measures we can obtain the nominal sales growth due to new products (g_2) and the nominal sales growth for old products ($\hat{g}_1$) as follows (for a while we suppress the subscript i for the firm):

$$g_2 = \frac{\textit{current sales new}}{\textit{past sales old}} = S \cdot \left(1 + \hat{g}\right)$$

$$\hat{g}_1 = \frac{\textit{current sales old-past sales old}}{\textit{past sales old}} = \hat{g} - g_2$$

Notice that if we want to proxy $\hat{g}$ and $\hat{g}_1$ with their corresponding values in real terms (g and g_1) we will use industry deflators π_1.[42, 43] Differently, g_2 cannot be

[42] Hence, $g = \hat{g} - \pi_1$ and $g_1 = \hat{g}_1 - \pi_1$.

[43] For manufacturing, they are constructed on the basis of the Producer Price Indices (PPI) at the 3-digits industry level for different sectors published by the INEC (the Ecuadorian statistical office). We used the variation in PPIs from 2009 to 2011. Due to lack of data, we apply the average PPIs for manufacturing to the service sector (as done in other related papers in this literature).

adjusted since we do not have information about new product prices and the difference with old product prices.

Once the previous growth rates are obtained, we calculate the dependent variable for our estimation equation in (9), $l_i - g_{1i}$, as the employment growth from 2009 to 2011 minus the real sales growth of old products (that is obtained from the difference between the nominal sales growth of old products $\hat{g}_{1i}$ and the industry deflators π_{1s} corresponding to the same period).

In Table C3.2, we present some descriptive statistics of relevant variables for our analysis. For firms' innovation statuses, we construct dummy variables for product, process, organizational and marketing innovations, and also for the corresponding exclusive categories. We also construct dummies for non-innovators and for all-type innovators. We observe from Table C3.2 that non-innovators represent around 36% of firms and also that the most common innovative activities among all firms in the sample are product (43%) and process (42%) innovations, although the percentage of firms performing marketing (25%) and organizational (24%) innovations is also quite high. Furthermore, employment growth for the period 2009-2011 of innovators is around one and a half times larger than that of non-innovators (there are not remarkable differences among product, process and marketing innovators, but the growth rate is larger for organizational innovators). Looking at the exclusive categories, employment growth is larger for all-type innovators. However, although the average sales growth during the period 2009-2011 is high for innovators, is even higher for non-innovators. This unexpected result very likely indicates that not all firms' sales evolution obeys to innovations and points out the necessity of performing an econometric analysis controlling for other firms' factors potentially affecting sales growth.[44] Further, looking at the disaggregated information about the average growth in sales of old and new products, we observe that for product innovators the growth rate of sales of new products is the most important component of their average growth in total sales, even obtaining that for only product innovators the contribution of average sales growth of old products to total growth is negative. This could be signaling some cannibalization of old products by new ones, although it is not a sufficient condition for this to happen.

Table C3. 2 Growth of employment and sales, 2009-2011[a]

Variables	% of firms (over Total)	Employment growth	Sales growth[b]	Sales Growth old products[b]	Sales growth new products[b]
d_prod	0.432	0.217	0.632	0.031	0.600
d_proc	0.421	0.219	0.670	0.208	0.462
d_org	0.239	0.272	0.738	0.300	0.437
d_mark	0.250	0.206	0.513	0.138	0.375
d_onlyprod	0.073	0.178	0.525	-0.019	0.544
d_onlyproc	0.065	0.169	0.813	0.813	0
d_onlyorg	0.036	0.189	0.291	0.291	0
d_onlymark	0.041	0.106	0.234	0.234	0
d_allinnov	0.071	0.270	0.561	-0.0815	0.642
d_noninov	0.358	0.148	1.179	1.179	0

Notes:
[a] Rates of growth for the whole period 2009-2011.
[b] Total sales growth, sales growth for old products and sales growth for new products.

Additionally, Table C3.3 reports mean tests comparing size of firms in 2011 with size of firms in 2009 and whether firms performing innovation activities are larger in 2011 than firms not performing them. It is obtained that firms are larger in 2011 than in 2009, and also that firms innovating are in 2011 larger than firms that do not innovate.

[44] There could also be the case that firms facing a more competitive market that threatens their sales are more keen on introducing innovations.

Table C3. 3 Mean test for employment by type of innovation

	Difference	Std. Err.
workers 2011 vs 2009	0.112 ***	0.006
d_prod (1) vs d_prod (0)	0.389 ***	0.051
d_proc (1) vs d_proc (0)	0.520 ***	0.051
d_mark (1) vs d_mark(0)	0.165 ***	0.059
d_org (1) vs d_org (0)	0.422 ***	0.060
d_allinnov (1) vs d_allinnov (0)	0.404 ***	0.100
d_noninov (1) vs d_noninov (0)	-0.343 ***	0.053

Notes:
H0 = difference 1 – difference 0; *, ** and *** significant at 10%, 5% and 1% level, respectively.

In our econometric analysis in section 3.5, we also include some controls that may affect firms' employment growth apart from variables directly derived from the theoretical model. First, we control for sector technological intensity through the inclusion of dummy variables according to the technological classification by the OECD (2006, 2007) for manufacturing and services. Following this classification, manufacturing is divided in High-technology industries, Medium-high-technology industries, Medium-low-technology industries and Low-technology industries. For the services classification we distinguish between Knowledge-intensive services and Less knowledge-intensive services. The original information in the survey follows the industry classification of the *ISIC Rev.4*. The level of disaggregation for manufacturing is 3-digits and for services 2-digits. However, a high level of industry disaggregation in combination with our cross-section sample size of 2,437 firms will generate multicollinearity problems in estimation.[45] Furthermore, notice that the model has differenced out whatever is firm-specific. Hence, the justification for including in the employment growth equation some industry controls is just to gain in flexibility by allowing the effects of industry dummies to change from the initial period to the final

[45] At the high level of disaggregation of sectors according to the *ISIC Rev.4* classification, we did not have variation of firms' choices with respect to innovation decisions in several cells.

period covered in the survey. In the dataset, the largest number of firms is concentrated in the low technology group in manufacturing (26.4%, being mainly integrated by firms in the food, beverage and tobacco sectors) and in the group of knowledge-intensive services in services (30.1%, with firms in services such as information, communication or finance, among others).

Second, we control for firms' size. On the one side, the Gibrat's law states that the proportional rate of growth of a firm is independent of its absolute size (Gibrat, 1931). On the other side, it does not exist a consensus about the validity of that law since in many studies is found that smaller firms grow faster (Audretsch *et al.*, 2004). For this purpose, as the Production Laws in Ecuador, Production Code 2010 and Regulation Production Code 2011 (Registro Oficial, 2010; Presidencia de la República del Ecuador, 2011), classify firms' size in four groups, we apply this classification to create four dummy variables corresponding to Micro, Small, Medium, and Large firms.[46] We obtain that according to this classification, 14.4% of our working sample of firms are classified as Micro, 44.7% as Small, 22.0% as Medium, and 19.0% as Large. It is important to remember that the NIAS survey does exclude firms with less than 10 employees.

Appendix C3.2 displays mean values and standard deviations for the relevant variables in our econometric analysis in Section 3.5.

[46] The four groups are: Micro firms (with sales under 100,000 USD), Small firms (with sales between 100,001 to 1,000,000 USD), Medium firms (1,000,001 to 5,000,000 USD), and Large firms (over 5,000,001 USD). Size dummies are related to information in the year 2009.

3.5. Results

3.5.1. Innovation and employment growth

We are interested in estimation of the empirical model in (9). Notice in this equation that by model construction even if sales growth of old products was moved to the right hand side as regressor, its coefficient is constrained to be one. Hence, we can still interpret results in terms of employment growth when our dependent variable is defined as $l_i - g_{1i}$, as in (9). Our empirical model includes four types of innovations: process, organizational, and marketing innovations, accounting whether firms perform or not these activities, and product innovations that are measured by firms' sales growth due to new products.[47] In Table C3.4 we present both the naïve OLS estimator and the instrumental variables one. The latter is estimated by combining the implied moment conditions through heteroscedastic GMM.[48] For interpreting our results, we will focus on the consistent estimates, that is the ones from the IV estimator (where the variable sales growth due to new products is instrumented). For process innovation, we obtain a negative and significant coefficient. According to the model, this obeys to an increase

[47] In our regressions presented in the chapter we define process innovations as a non-exclusive category as regards product innovations. The reason is that defining this variable as only process innovations keeps the sign of our estimates but does not render statistical significance, probably hindering a problem of data limitations in identifying the effects of process innovations on employment growth due to the small sample of firms that only perform this activity. Additionally, this approach would soften a potential problem in the interpretation of the estimated coefficient for the variable sales growth due to new products, which might also capture part of the effect of process innovation when performed simultaneously with product innovation. This would contribute to the non-significance for a process only innovation dummy. One limitation of surveys that also applies to CIS type ones is that it is impossible to know which process innovations correspond to old or new products.

[48] Efficiency in GMM is robust to heteroscedasticity of unknown form.

over time in efficiency in the production of old products due to the introduction of process innovation, what requires less labor (*displacement effect*). A similar result for process innovation is obtained in Dachs *et al.* (2017) for European countries. In particular, we obtain that employment growth of process innovators is about 0.25 percentage points smaller. It seems quite reasonable to think that when firms introduce process or organizational innovations they try to gain in efficiency. However, for organizational innovation, although the sign in also negative is insignificant (Dachs *et al.*, 2017, obtain also a negative sign but significant; Peters *et al.*, 2013, obtain a negative but insignificant coefficient).

Table C3. 4 The effects of innovation on employment growth

Dependent variable:	(1)	(2)
Employment growth ($l-g_1$)[a]	OLS Estimation	IV Estimation[b]
Process innovation	0.381*	-0.246*
	(0.075)	(0.099)
Organizational innovation	0.157	-0.107
	(0.438)	(0.468)
Sales growth due to new prod. (g_2)	-0.249	1.444**
	(0.394)	(0.050)
Marketing innovation	0.355*	0.324**
	(0.072)	(0.050)
Micro firms$_{2009}$	-0.171	-0.619***
	(0.504)	(0.004)
Small firms$_{2009}$	-0.663	-0.781
	(0.282)	(0.194)
Medium firms$_{2009}$	0.123	0.004
	(0.285)	(0.956)
OECD_HIGH	1.118	1.187
	(0.363)	(0.283)
OECD_MED_HIGH	1.401	1.155
	(0.303)	(0.297)
OECD_MED_LOW	1.266	1.251
	(0.358)	(0.286)
OECD_LOW	1.254	1.176
	(0.337)	(0.285)
OECD_KNOWLEDGE	1.462	1.316
	(0.289)	(0.255)
Constant	-1.229	-1.112
	(0.350)	(0.322)
Observations	2,437	2,437
Hansen test Chi^2 (3)		0.806
P-value Hansen test[b]		0.841

Notes:
*, ** and *** significant at 10%, 5% and 1% level.
[a] Coefficients and p-values (in parenthesis) robust to heteroscedasticity. Both regressions include size and sector dummies.
[b] Method: GMM instrumental variables estimation. The four instruments *increased range of products*, *clients as information source*, *reaction to the market* and *replacement of outdated products*, are used. Ho: $E(Z,u) = 0$, non-rejected.

The strongest effect of innovation on employment growth is found for product innovations, since the variable sales growth due to new products has a significant and positive coefficient that is larger than one. According to the model, with the estimation of β we get an estimate of the relative efficiency in the production of old products with respect to new products. Thus, our obtained results for Ecuador indicate that old products are produced more efficiently than new ones. For this reason, a *displacement effect* of workers due to higher productivity is not in operation, but contrarily, we may conclude that the increase in sales due to new products generates employment growth.[49] This result for Ecuadorian firms is similar to the one obtained in Crespi and Tacsir (2012) for Argentina, Chile and Costa Rica, Monge-González *et al.* (2011) for Costa Rica, and de Ejalde *et al.* (2011, 2015) for Argentina. For Ecuador, the estimated coefficient indicates that a 1% increase in sales due to new products generates a 1.4% increase in *gross* employment (this is a relative efficiency/productivity effect on employment). As the model coefficients do not allow identification of the extent at which new products displace existing ones, to say something about the *net* employment effect of product innovation we require the decomposition methodology of employment growth presented in the next section.

As regards marketing innovation the estimated coefficient is positive and significant. If the dominant direct (*gross*) effect of marketing innovation on employment growth was a *displacement effect* of labor due to the increase in efficiency over time in the production of old products, the estimated coefficient for this variable would have

[49] The OLS estimator for this variable was insignificant, consistent with the expected problem of attenuation bias in a variable such as g_{2i} that is subject to measurement error.

been negative. However, if the dominant *gross* effect is positive, as is our particular case for Ecuador, it might suggest that firms financially constrained are alleviated with the likely increase in profits from the encouragement of consumers' perceived quality, reputation, branding and consumers loyalty by the performance of marketing innovative activities. One performed robustness check excluding marketing innovation from the regression does not noticeably affect to the estimated coefficients for process or organizational innovations (α_1 and α_2, respectively). However, differently, it increases the estimate of β from 1.44 to 1.64, which might suggest the existence of an overestimation omitted variable bias in this coefficient when marketing innovation is positively correlated with nominal growth in production due to new products and the regression does not include marketing innovation as a regressor. Some evidence in the direction of marketing innovation increasing profits by increasing prices of new products as regards initial prices of old products is obtained by comparing results of a regression of g_{2i} (nominal growth in sales due to new products) on the marketing dummy and controlling for industry technological sectors and size dummies, with results from the same regression but including the four instruments considered in this chapter as extra regressors for explaining g_{2i}. The second regression can be considered as cleaning g_{2i} from prices and, hence, getting a proxy for real growth in sales due to new products. In the first regression we obtain that the coefficient for the marketing innovation dummy is positive and statistically significant (0.151, p-value=0.000 under robust standard errors), and in the second regression we obtain that it is not statistically significant (p-value= 0.524 under robust standard errors). This works in favor of marketing innovation affecting the nominal growth rate in sales due to new products but not the real growth rate in sales due to new products. As the difference between the two growth rates comes from the ratio P_{22}/P_{11}, the obtained results indicate that marketing innovation increases this ratio of prices (hence, it favors prices for new products).

The constant in the model (α_0), although with the expected negative sign, is statistically non-significant, which may indicate that the efficiency in the production of old products from 2009 to 2011 does not evolve simply with the passage of time by mechanisms such as "learning by doing" or spillovers. However, although technological industry dummies are not statistically significant, the size dummy for Micro firms has a negative and statistically significant coefficient, indicating that for Micro firms in particular there exists an increase over time in efficiency of production of old products that may obey to the previously indicated mechanisms, and that justifies less labor requirements.

3.5.2. Testing instruments validity

In this section, we are focused on testing instruments validity. On the one side, they should be correlated with the expected sales growth due to new products. On the other side, they should be uncorrelated with the error term in expression (9), our empirical estimation equation. The implementation of the first testing procedure requires a first step estimator of a reduced form regression where the dependent variable is (nominal) sales growth due to new products and the regressors are the other regressors in (9) plus the four external instruments *increased range of products*, *clients as information source*, *reaction to the market* and *replacement of outdated products*. The results of this regression are displayed in Table C3.5. As we can see at the bottom of that table, external instruments are both individually (with positive sign) and jointly significant (the F-test has a p-value=0.000), which indicates they are not weak instruments. The F-statistic in the first stage regression is larger than 10, indicated as a threshold value in Stock and Yogo (2005). For the implementation of the second testing procedure, as we have four potential instruments and one variable to be instrumented, we can perform a χ^2 Hansen test of overidentifying restrictions with the excess of instruments. The result of this test confirms that our instruments are not rejected (with a p-value=0.841, see at the bottom of Table C3.4). The two testing procedures support our choice of instruments as adequate for our setting.

Table C3. 5 First stage regression for IV method

Dependent variable: Sales growth due to new prod. (g_2)[a]	OLS Estimation
Process innovation	0.0503
	(0.272)
Organizational innovation	0.095*
	(0.071)
Marketing innovation	-0.044
	(0.300)
Micro firms$_{2009}$	0.239***
	(0.000)
Small firms$_{2009}$	0.107***
	(0.003)
Medium firms$_{2009}$	0.058**
	(0.037)
OECD_HIGH	-0.043
	(0.531)
OECD_MED_HIGH	0.0456
	(0.592)
OECD_MED_LOW	-0.053
	(0.383)
OECD_LOW	-0.041
	(0.467)
OECD_KNOWLEDGE	-0.0263
	(0.659)
Instruments (IVs)	
Increased range of products	0.084***
	(0.000)
Clients as information source	0.120**
	(0.020)
Reaction to the market	0.078*
	(0.100)
Replacement of outdated products	0.118**
	(0.025)
Constant	-0.080**
	(0.018)
Observations	2,437
R-squared	0.111
Test of week instruments	
F-test for significance of IVs, F(4, 2421)	31.41
p-value	0.000

Notes:
*, ** and *** significant at 10%, 5% and 1% level.
[a] Coefficients and p-values (in parenthesis) robust to heteroscedasticity.

3.5.3. Average employment growth decomposition

In this section, using coefficient estimates from (9) by the IV approach, we implement a decomposition methodology of employment growth to disentangle which percentage of employment growth corresponds to different components in (9). Acknowledging that α_0 in (9) incorporates the effects of industry and size dummies in employment growth, and moving back sales growth due to old products to the right hand side of the expression, (9) can be written as:

$$(10)\quad l_i = \left(\alpha_{00} + \sum_j \alpha_{0j} \cdot d_{industry_j} + \sum_s \alpha_{0s} \cdot d_{size_s}\right) + \alpha_1 \cdot Process_i + \alpha_2 \cdot Organizational_i + \alpha_3 \cdot Marketing_i + g_{1i} + \beta \cdot g_{2i} + \varepsilon_i$$

where α_0 in (9) is equal to $\alpha_{00} + \sum_j \alpha_{0j} \cdot d_{industry_j} + \sum_s \alpha_{0s} \cdot d_{size_s}$ in (10). In expression (10) we can replace coefficients by their estimates and write it in means over the subscript *i* to get:

$$(11)\quad \begin{array}{ccccccccccccccc} \bar{l} & = & \hat{\alpha}_0 & + & \hat{\alpha}_1 \cdot \bar{P} & + & \hat{\alpha}_2 \cdot \bar{O} & + & \hat{\alpha}_3 \cdot \bar{M} & + & \bar{g}_1 & + & \hat{\beta} \cdot \bar{g}_2 \\ 18.5 & = & -57.9 & - & 10.3 & - & 2.6 & + & 8.1 & + & 43.7 & + & 37.5 \end{array}$$

where in the first row the bars on the top of variables denote mean values, the hats on coefficients indicate that they have been replaced by their estimates, there is a zero mean residual component, and *P*, *O* and *M* are the abbreviated names for process, organizational and marketing innovations, respectively. In the second row we plug the values obtained when already substituting the estimated coefficients and the mean values of the corresponding variables in the estimation sample. Next, we further decompose in (11) the average contribution to employment growth from old products ($\bar{g}_1$) for firms that are non-product innovators and for firms that are product innovators. Doing that, we obtain that the 43.7 percentage points in which the growth of old products contributes to employment growth comes from the 47.6 percentage points from non-product innovators and from the -3.9 percentage points from product innovators. Hence, expression (11) becomes:

$$
\begin{array}{llllllllllllllll}
(12) & \bar{l} & = & \hat{\alpha}_0 & + & \hat{\alpha}_1 \cdot \bar{P} & + & \hat{\alpha}_2 \cdot \bar{O} & + & \hat{\alpha}_3 \cdot \bar{M} & + & N\bar{P}D \cdot \bar{g}_{1,NPD} & + & Y\bar{P}D \cdot \bar{g}_{1,YPD} & + & Y\bar{P}D \cdot \hat{\beta} \cdot \bar{g}_{2,YPD} \\
 & 18.5 & = & -57.9 & - & 10.3 & - & 2.6 & + & 8.1 & + & 47.6 & - & 3.9 & + & 37.5
\end{array}
$$

where *NPD* and *YPD* are the share in the estimation sample of non-product and yes-product innovators, respectively. Notice that $\hat{\beta} \cdot \bar{g}_2$ in (11) has been substituted in notation in (12) by $Y\bar{P}D \cdot \hat{\beta} \cdot \bar{g}_{2,YPD}$ since the two are identical because $\bar{g}_{2,NPD} = 0$ (that is, non-product innovators have by definition zero growth in sales due to new products).

Let us now interpret the decomposition results displayed in the second row of (12). The first element, $\hat{\alpha}_0$, measures the contribution to employment growth of changes in efficiency in the production of old products that are not coming from the firm's own innovations. This general productivity trend contribution includes the general industry and size contributions. The negative value of this component, jointly to the results from Table C3.4, reflects an increase in efficiency (labor saving) in the production of old products for Micro firms (independent of this type of firms own innovations). The second and third elements ($\hat{\alpha}_1 \cdot \bar{P}$ and $\hat{\alpha}_2 \cdot \bar{O}$) measure the contribution to employment growth of changes in efficiency in the production of old products that are coming from the share of process and organizational innovators, respectively. Their negative values point to an increase in efficiency (labor saving) in the production of old products as a consequence of introducing process and organizational innovations. However, taking into account the results from Table C3.4, this is statistically true for process innovation (since the estimated coefficient for organizational innovation is negative but non-significant). The fifth element, $N\overline{P}D \cdot \overline{g}_{1,NPD}$, measures the contribution to employment growth coming from the growth in production of old products for the share of non-product innovators. The magnitude of the positive value of this component indicates that non-product innovators enjoy an increase in demand of old products (hence, they do not seem to suffer from business stealing effects from product innovators but, differently, they probably face an elastic demand that reacts to likely price reductions for old products). The sixth element, $Y\overline{P}D \cdot \overline{g}_{1,YPD}$, measures the contribution to employment growth coming from the growth in production of old products for the share of yes-product innovators. The negative value obtained for this term captures the indirect negative effect on demand for old products that exerts in firms the introduction of new products (hence, cannibalization instead of complementarity in the firm between old and new products). The seventh element, $\hat{\beta} \cdot \overline{g}_2 = Y\overline{P}D \cdot \hat{\beta} \cdot \overline{g}_{2,YPD}$, measures the contribution to employment growth from the growth in sales due to new products of the share of product innovators. The value of this component is positive and economically relevant, indicating that firms increasing sales due to new products contribute to employment growth. This result is explained by the degree of innovation success of product innovations, as measured by $\overline{g}_{2,YPD}$, by a higher relative efficiency in the production of old products as regards to new ones ($\hat{\beta} > 1$) and by the share of product innovating firms ($Y\overline{P}D$). Finally, the forth element, $\hat{\alpha}_3 \cdot \overline{M}$, has a positive value and, hence, gives support to the idea of financially constrained firms alleviating their constraints in hiring by the likely increase in profits generated by an improvement in perceived quality, reputation, branding and consumers loyalty (which increase relative prices for new products as regards the initial price for old products).

Before performing the decomposition in this subsection, we were only able to say something about the *gross* effects of product innovation on employment growth, that is $\hat{\beta} \cdot \bar{g}_2$. Now, however, we can speak about the *net* contribution of product innovation to employment growth, which is determined by $Y\bar{P}D \cdot \bar{g}_{1,YPD} + Y\bar{P}D \cdot \hat{\beta} \cdot \bar{g}_{2,YPD}$, that is the contribution to employment growth due to sales growth of old products for product innovative firms plus the contribution to employment growth due to sales growth due to new products for product innovative firms. The *net* effect takes into account the degree of cannibalization of old products inside of firms that introduce new products.

The summary of results from the decomposition analysis is displayed in Table C3.6.

Table C3. 6 Decomposition of employment growth

Variables	Percentage
Employment growth ($\bar{l}$)	18.5
General productivity trend old products ($\hat{\alpha}_0$)	-57.9
Productivity effect of process innovations ($\hat{\alpha}_1 \cdot \bar{P}$)	-10.3
Productivity effect of organizational innovations $\hat{\alpha}_2 \cdot \bar{O}$	-2.6
Effect of output growth of old products (for non-product innovators, $N\bar{P}D \cdot \bar{g}_{1,NPD}$)	47.6
Net employment effects of product innovations:	33.6
Effect of output growth of old products (for product innovators, $Y\bar{P}D \cdot \bar{g}_{1,YPD}$)	-3.9
Effect of the increase in production due to new products ($Y\bar{P}D \cdot \hat{\beta} \cdot \bar{g}_{2,YPD}$)	37.5
Effect of the increase in profits from marketing innovations (consumers' willingness to pay, $\hat{\alpha}_3 \cdot \bar{M}$)	8.1

3.5.4. Two dimensions in the quality of employment growth generated by innovation: labor skills and wages

In this section, we use information on two dimensions of quality of labor such as skill composition of employment and wages. We are interested in checking whether innovation activities not only encourage employment growth but also correlate positively with the skill composition of labor in the firm and the average wages per employee at the firm level. Unfortunately, the Ecuadorian National Innovation Activities Survey does not allow us to know what portion of employment changes from 2009 to 2011 correspond to different levels of skills for employees. However, the survey provides a classification of employment by skills that corresponds to the year 2011. Additionally, the survey does not provide either information on wages. This means that for the second part of our analysis in this subsection, in which we are interested in checking whether innovation not only is positively related with skills but also with the possibility of workers earning higher wages, we will use information coming from a different dataset that contains this information. This is the last Ecuadorian Economic Census (2010, with firms' information corresponding to 2009).[50]

For the first part of our analysis in this subsection, we use a definition of skilled labor that follows the one in de Ejalde *et al.* (2015). They define as skilled labor the percentage of employees that have more than basic education (this includes primary and secondary education). According to the information in our survey, this percentage includes employees with PhD degree, Master degree, Bachelor degree, Specialists and Technicians (these refer to university degrees or tertiary education related to technical professions). This variable transformed in logs is used as dependent variable in two

[50] See Chapter 2 and Rodríguez-Moreno and Rochina-Barrachina (2015) for more details about this dataset.

different specifications. In the first specification, we use as the main regressor the predicted value of the innovative employment growth that comes from estimation of expression (9) by instrumental variables. We add as control variables the dummies for firms' size classes and a dummy variable controlling for highly intensive knowledge sectors. In the second specification, we replace the regressor of innovative employment growth by the same innovation variables previously employed in this chapter to study the effects of different types of innovations on employment growth. These are the dummies for process innovation, organizational innovation, marketing innovation and the sales growth due to new products. The same controls than in the previous specification are also included here. The results from estimating both specifications are in columns 1 and 2, respectively, in Table C3.7. Our aim under both specifications is the performance of an analysis linking innovation measures such as innovative employment growth or innovation output variables, that correspond in the survey to the period that goes from 2009 to 2011, to the firms' composition of employment skills in 2011, in order to check whether innovation contributes to a higher percentage of skilled (qualified) employees. The first specification in column 1 of Table C3.7 is estimated by OLS. The second specification, in column 2, is estimated by the IV method, since we also instrument the variable sales growth due to new products (as previously in this chapter). Results in the two columns point into the same direction. On the one side, innovative employment growth has a positive effect on the skill composition of the firm's labor force. On the other side, this positive relationship comes from the positive effect on skills composition associated to sales growth due to new products. Notice that the coefficient for this variable is positive and significant in column 2 of Table C3.7. Differently, the performance of process innovation is negatively related to a higher skill labor composition. Finally, the other two types of innovations, namely organizational innovation and marketing innovation, do not render any statistically significant effect on the firms' skill composition.

Table C3. 7 Effects of innovation on firms' skill labor composition and wages

Dependent variables[a]	(1)[b] Skill labor (log%) OLS	(2)[c] Skill labor (log %) IV	(3)[d] Log wages per worker OLS	(4)[e] Log wages per worker OLS
Innovative employment growth	0.002***			
	(0.002)			
Process innovation		-0.224**		
		(0.023)		
Organizational innovation		0.131		
		(0.131)		
Sales growth due to new prod. (g_2)		0.415**		
		(0.039)		
Marketing innovation		-0.014		
		(0.852)		
(Yes/no) R&D			0.855***	
			(0.000)	
Log R&D expenditure				0.133***
				(0.000)
OCDE_GROUP_HIGH[f]	1.779***	1.750***	0.599***	0.597***
	(0.000)	(0.000)	(0.000)	(0.000)
Micro firms	0.347***	0.270**	-2.126***	-2.107***
	(0.002)	(0.032)	(0.000)	(0.000)
Small firms	0.093	0.053	-0.656***	-0.643***
	(0.287)	(0.557)	(0.000)	(0.000)
Medium firms	-0.106	-0.120	0.925***	0.921***
	(0.281)	(0.228)	(0.000)	(0.000)
Constant	-1.329***	-1.330***	10.506***	10.487***
	(0.000)	(0.000)	(0.000)	(0.000)
Observations	2,437	2,437	126,737	126,737
R-squared	0.222	0.202	0.406	0.409
Hansen test Chi^2 (3)		3,35		
P-value Hansen test[g]		0,34		

Notes:
*, ** and *** significant at 10%, 5% and 1% level.
[a] Coefficients and standard errors (in parenthesis) robust to heteroscedasticity.
[b,c] The dependent variable is the log transformation of the percentage of the firm's skill workers. Skill workers are employees with PhD, master, university degree, specialists and technicians as level of education.
[d,e] Log wages per employee and all the information about R&D performance and expenditures for these regressions is taken from the last Ecuadorian Economic Census (2010).
[f] Following the OCDE classification for manufacturing and services as regards knowledge intensity, we have created a dummy variable with value 1 if the sector belongs to the high classification for manufacturing and to the one of knowledge intensive sectors for services.
[g] Method: GMM instrumental variables estimation. The four instruments *increased range of products*, *clients as information source*, *reaction to the market* and *replacement of outdated products*, are used. Ho: $E(Z, u) = 0$, non-rejected.

In the second part of our analysis in this section, our purpose is disentangling whether innovation not only contributes to changing employment over time and skill composition of the firms' labor force, but also contributes to higher quality jobs in terms of wages per employee for innovative firms. As we already mentioned above, the survey used in this chapter lacks information on wages. Therefore, to illustrate this part of the analysis with firm-level data, we use another dataset with firm-level data for Ecuadorian firms. This is the last Ecuadorian Economic Census (2010). The variable wages per employee is calculated with the information in the Census about workers and total remuneration. The innovation information in the Census is more limited than in the Ecuadorian National Innovation Activities Survey, as it only includes a question about firms performing or not R&D and another question about the amount invested in R&D.

In the final two columns of Table C3.7, we include the regression results from estimation of log wage equations where the main variable of interest is either a dummy variable for the performance of R&D activities or the log of the R&D expenditure. We also add the same controls than for the skill labor specifications as regards firms' size dummies and highly technological group of sectors. The results for the main variables in both columns indicate that being an innovative firm is positively related with higher wages per employee. Although information about these aspects that may be considered as two dimensions of quality of the labor force is limited in our two employed datasets, we take results in Table C3.7 as some evidence about innovative activities not only affecting employment growth in the economy, but also positively influencing the quality of generated jobs in terms of skills of human capital and wages. As regards control variables in Table C3.7, it is interesting to highlight that firms belonging to highly intensive in knowledge sectors have both a higher proportion of skill workers and also pay higher wages per worker.[51] Furthermore, medium firms in terms of size pay higher wages, followed by large firms, while small and, specially, micro firms are the ones

[51] In fact, the dummy controlling for this type of sectors captures the "*most innovative*" sectors in manufacturing and services altogether.

paying lower wages. Surprisingly, micro firms have a higher percentage of skill labor, probably indicating that skills for this group are more than proportional to firm's size.

3.6. Conclusions

In this study we try to explain the effects over firms' employment of innovation activities by firms. For this purpose, we use the methodology in Harrison *et al.* (2014). This type of methodology has been used in other country studies but it has never been applied to the Ecuadorian economy. The dataset employed is the National Innovation Activities Survey 2013 (with firm-level data corresponding to the period 2009-2011). Differently to Harrison *et al.* (2014), we introduce four types of innovations (product, process, marketing and organizational) to measure separately their effects over employment. It is important to highlight that this is the first research that considers marketing as a different innovation type to be considered separately in the context of the Harrison *et al.* (2014) model.

Our results indicate that different types of innovations may have different effects on employment. Process innovation by increasing production efficiency over time decreases firms' demand for labor (*displacement effect*). Firms in homogeneous industries might be interested in becoming more competitive to survive in such environments by the introduction of process innovations. However, organizational innovation does not display a statistically significant effect on employment. Differently, growth in sales due to new products generates a *gross* increase in firms' labor demand since efficiency in the production of old products is higher than in the production of new ones (the opposite of a *displacement effect*) and since firms need to increase the number of employees to cover this new "demand". In addition, the *net* effect of product innovation on employment growth, which takes into account a certain degree of cannibalization of old products by new ones in product innovative firms, is still positive, large and highly significant, although smaller than the *gross* effect. This evidences that product innovators suffer from a decrease in demand of old products (in line with Schumpeter's, 1942, theory about creative destruction). However, we do not find evidence in favor or a business stealing effect from product innovators on sales growth for non-product innovators. Finally, we find evidence about marketing innovation also increasing employment growth by very likely increasing firms' profits through the increase in prices of new products as regards old ones. The effect of marketing innovation on employment growth represents a novelty explored in this chapter, since previously related papers do not consider this type of innovation and its separated effect on employment.

Overall, the positive effects of innovation on employment (from product and marketing innovations) exceed the negative ones (from process innovation, and from some cannibalization of old products by new ones inside product innovative firms).

In a second set of supplementary results in the chapter where we try to find some evidence about the quality of generated jobs, we find that innovative firms require higher proportions of skilled labor (driven by the success of product innovations as measured by sales growth due to new products) and pay higher average wages *per* employee. Process innovation seems to have a skill-bias effect in favor of unskilled labor. Hence, it seems that process innovations in Ecuador are targeting improvements in efficiency of more repetitive, automatic and simple tasks, which are not so demanding of skills. This makes compatible process innovation not only displacing labor but making it in a bias way against labor force with higher skills. Differently, product innovation in Ecuador seems to be related to more complex innovations that probably in the short and medium run are produced less efficiently than old products but require more skilled labor. This works in favor of product innovation both affecting positively employment growth and making this growth bias towards more skill workers.

To sum up, innovation not only has *net* employment effects in the economy, but we also find some evidence in favor of innovative activities by firms also positively influencing the quality of generated jobs in terms of skills and wages.

This type of study is highly relevant for a developing country like Ecuador, where it is not widely spread among firms the performance of technological activities in a highly intensive way. For politicians it might be interesting to know that both product and marketing innovations contribute to employment creation at least in the short and medium run (since our temporal horizon covers a period of three years), that product innovations also put pressure on higher skills on human capital that should be available for the economy, and that being innovative in general is positively associated to the possibility of workers earning higher average wages. For a country with not too much experience in "innovation culture" this type of studies contributes to highlight, with the support of empirical evidence, the benefits from innovation and the need to promote it.

Our study does not answer the question about where do more skilled workers for product-innovating firms come from, but provides some interesting hints about the possibility of part of them coming from firms that introduce process innovations, mainly affecting old products that have already larger possibilities to be more automatized in the short and medium term than new products. This points to an interesting dynamic process to research about in which process innovation increases efficiency in the production of old products, displaces labor mainly against more skilled workers but, product innovation more than compensates the previous labor displacement and works in favor of skill labor. This is a going on history, since new products today will become old products tomorrow, that highlights the joint relevant role of process and product innovations to make sustainable simultaneously for a society improvements of efficiency in production with employment growth, generation of jobs with higher skills of the labor force and associated to higher wages.

Appendix C3. 1 Evidence from several countries on the impact of innovation on labor following the Harrison *et al.*(2014) methodology

Country *1. European Countries*	α_0	Sales growth new prod. (g2) β	Process innov. α_1	Organiz. innov. α_2	Market. innov. α_3	Paper
Italy	-2.80***	0.95***	-1.22*	n/a	n/a	Hall et al. (2008). The paper only includes manufacturing.
20 European Countries	-20.889*** -27.574***	0.989*** 0.968***	-2.475*** 0.308	-0.621 -0.939	n/a	Peters et al. (2013). We reproduce here results in columns 4 and 6 of Table 9 in the paper (first row manufacturing, second row services). Countries included: Bulgaria, Cyprus, Czech Republic, Germany, Estonia, Spain, France, Hungary, Italy, Lithuania, Luxembourg, Latvia, Malta, Netherlands, Portugal, Romania, Slovenia, Slovakia, UK, and Ireland.
16 European Countries	-14.015*** -10.375***	1.011*** 0.903***	-1.973** -1.603	n/a	n/a	Dachs and Peters (2014). We reproduce here results in column 4 of Table 3 in the paper (first row manufacturing, second row services). Countries included: Bulgaria, Czech Republic, Denmark, Estonia, Spain, France, Greece, Hungary, Italy, Luxembourg, Latvia, Norway, Portugal, Romania, Slovenia, and Slovakia.
28 European Countries	11.486***	0.676***	-0.001	0.307***		Damijan et al. (2014). Organizational and Marketing innovations are jointly treated. We reproduce here results in column 2 of Table 6 in the paper (joint results for manufacturing and services).
France	-3.52*** -5.25**	0.98*** 1.16***	-1.31 -1.45	n/a	n/a	Harrison et al. (2014). We reproduce here results in B and D of Table 3 in the paper (first row manufacturing, second row services).
Germany	-6.95*** -3.36	1.01*** 0.92***	-6.19** 1.54	n/a	n/a	
Spain	-6.11*** -4.04*	1.02*** 0.99***	2.46 -0.38	n/a	n/a	
UK	-6.30*** -5.51***	0.99*** 1.05***	-3.51* 3.21	n/a	n/a	
26 European Countries	-67.158*** -15.094***	0.991*** 1.003***	-1.665** -1.816*	-2.284*** -1.393**	n/a n/a	Dachs et al. (2017). We reproduce here results in Table 4 of the paper (first row for upturns and second row for downturns; the paper only includes manufacturing).
2. Latin American Countries						
Chile	-0.790**	0.545***	0.096	n/a	n/a	Benavente and Lauterbach (2008). We reproduce here results from Table 4 (Panel C) in the paper (the paper includes jointly manufacturing, mining and power industry).
Chile	-1.989	1.740***	0.297	n/a	n/a	Álvarez et al. (2011). We reproduce here results in column 1 of Table 8 in the paper (the paper only includes manufacturing).
Costa Rica	-12.160**	1.015***	18.413*	n/a	n/a	Monge-González et al. (2011). We reproduce here results in column 4 of Table 8 in the paper (the paper only includes manufacturing).
Argentina	-0.994	1.170***	1.398	n/a	n/a	de Elejalde et al (2011). We reproduce here results in column 4 of Table 12 in the paper (the paper only includes manufacturing).

sArgentina	-0.994	1.170***	1,398	n/a	n/a	Crespi and Tacsir (2012). We reproduce here results in columns 1-4 of Table 6 in the paper (the paper only includes manufacturing).
Chile	-2,016	1.751***	0.333	n/a	n/a	
Costa Rica	-12.160**	1.015***	18.413*	n/a	n/a	
Uruguay	1.402**	0.961***	-2.716**	n/a	n/a	
Argentina	n/a	1.151***	1.252	n/a	n/a	de Elejalde et al. (2015). We reproduce here results in column 1 of Table 3 in the paper (the paper only includes manufacturing).
Uruguay	1.544**	0.964***	−2.610**	n/a	n/a	Aboal et al. (2015). We reproduce here results in column 4 of Table 2 in the paper (the paper only includes manufacturing).

Appendix C3. 2 Summary Statistics

Variable	Mean (sd)
Employment growth (l , not in %)	0.185
	(0.540)
Sales growth of old prod. (g_1, not in %)	0.437
	(15.012)
Process innovation dummy	0.422
	(0.494)
Organizational innovation dummy	0.239
	(0.427)
Marketing innovation dummy	0.250
	(0.433)
Sales growth due to new prod. (g_2, not in %)	0.260
	(0.765)
Micro firms	0.144
	(0.351)
Small firms	0.447
	(0.497)
Medium firms	0.220
	(0.414)
Large firms	0.190
	(0.392)
OECD_HIGH	0.009
	(0.095)
OECD_MED_HIGH	0.048
	(0.215)
OECD_MED_LOW	0.158
	(0.365)
OECD_LOW	0.264
	(0.441)
OECD_KNOWLEDGE	0.301
	(0.459)
OECD_LESS_KNOWLEDGE	0.219
	(0.414)
Increased range of products	1.783
	(1.763)
Clients as information source	0.362
	(0.481)
Reaction to the market	0.190
	(0.392)
Replacement of outdated products	0.241
	(0.428)
Observations	2,437

Chapter 4: Public support effectiveness on innovation effort in Ecuadorian firms

4.1. Introduction

Countries are in general interested in ascertaining the effectiveness of public funds to encourage or reinforce firms' innovation efforts. On the one hand, governments take into consideration several instruments of public support for promoting innovation. On the other hand, there are the private motivations to innovate. The firms' aims to innovate have been largely discussed on the theoretical literature about firms' innovation activities (see Schumpeter, 1942, Arrow, 1962, or Aghion *et al.*, 2005), with special focus on the relationship between market structure and innovation. However, Nelson (1959) argues, in relation to the scientific research, that firms and government offices aims are divergent in evaluating the returns from innovation. For instance, the *"innovative firm"* could be interested in getting appropriability instruments to increase its gains whenever the market is concentrated, but the public offices would encourage innovation likely in situations where knowledge spillovers are important, and where innovation can promote a competitive market with relevant "*social impact*". Therefore, for the governments could be hard to design a mechanism to increase the innovation performance of firms when there are sometimes non-coincident aims when pursuing innovative activities.

Another important question in this field of analysis is: why firms require some type of public support to innovate? The answer to this question, in some cases, could be related with the uncertainty about returns to R&D activities. Firms' R&D investments are related to the necessity of human capital, laboratories, and another inputs that in some industries represent very high expenditures. Both high costs and the uncertainty of returns to these activities can discourage many firms to invest in innovation, being this problem even stronger for firms in developing countries, where experience in innovation activities is scarcer and more novel. In such countries, there can be a role for supporting and financing part of these activities as a mechanism to encourage their future self-sustainable development. For firms, the sources to finance innovation expenditures may come either from the private sector (own resources, corporate resources or bank lending) or from the public sector (through grants, cheaper lending or some support programs). As explained by David *et al.*(2000), in the firms' decisions about innovative investments enter both issues related to the marginal costs of capital and to the rates of return from innovation. The authors explain how *"macro conditions"* such as the existence of bond markets or the availability and terms of venture capital, influence the cost of capital. They also explain that, differently, variables related with demand and appropriability conditions are the ones that influence the rates of return. Lederman and Maloney (2003) explain that in developing countries the R&D projects to be performed have a higher requirement in terms of returns to investment, since these countries probably face higher marginal costs of capital. Hence, for projects to be profitable, rates of return of projects should be higher. Therefore, one argument in favour of the provision of public support to innovation investments in developing countries is to reduce through this instrument the marginal cost of capital for firms to invest in R&D. Hall and Lerner (2010) do a literature review about financial constrains to R&D investments. They show evidence about external debt not being a convenient source for financing firms' R&D activities, the reason being that in some cases the external cost of capital is higher than the internal to the firm, but sometimes firms cannot generate the necessary cash flow to invest in R&D. In front of this evidence, it may be argued that the public sector may help firms perform R&D by financing part of it through subsidies or low-interest rate loans. Huergo *et al.* (2016) demonstrate with Spanish data that the provision of low-interest rate loans is relevant for firms' R&D investments.

In agreement with the previous paragraph, the governments seem to have an important role in promoting the R&D investment of firms (see also Hall and Van Reenen, 2000, for a literature review about fiscal incentives to R&D). The principal public policy mechanisms to generate incentives for innovation are the following: Tax incentives, special programs, subsidies, grants and public support funds. About them, economists have not yet a clear evidence of effectiveness of this type of instruments to promote innovation and increase the aggregate R&D at the country level. For example, Bloom *et al.*(2002) analyse the tax incentive mechanism in nine OECD countries (Australia, Canada, France, Germany, Italy, Japan, Spain, United Kingdom, and USA) with different structure and amount of benefits. They argue that there can be differences between countries that could modify the effectiveness of this type of instrument, although their evidence shows in general an increase in R&D intensity. In addition, Zúñiga-Vicente *et al.* (2014), in their survey about public subsidies, show large evidence of that effect also at the firm level. They found evidence in the literature, with more emphasis in developed countries, about public subsidies creating an additional effect (increase) in the R&D private expenditure. But, on the other hand, they also find evidence about government support substituting part of the "potential" R&D private effort. Moreover, Busom *et al.* (2014) compare the effects of tax incentives and subsidies for different size groups and ages of firms. They found that subsidies are a better option of support for young firms which had a short experience in R&D.

Hence, in related literature, there can be a double relationship between R&D private expenditure and the provision of public support. On the one hand, there is research confirming the existence of a *crowding out* effect. That means that firms reduce or replace their own R&D investment/effort by the public funds. For example, suppose one firm would plan invest some amount of money in R&D activities in the absence of public support, but when the government allocates money to support the innovation, with the purpose of increasing the *total* investment on R&D in the economy, this firm reduces its private investment or effort in innovation that otherwise would have performed without the existence of the subsidy. When this is the case, we call this situation as *crowding out* effect of the public policy. Under this scenario, the subsidy reduces the private effort, and the total firm's effort or investment will be lower than the sum of the public contribution plus the private effort of the firm in case of non-existence of the subsidy. On the other hand, there is a different scenario in which the private effort is larger with the subsidy than it would have been without the subsidy. In this case, the subsidy increases private effort, and the total firm's effort will be higher than the sum of the public contribution plus the private effort of the firm without a subsidy. We are now in the presence of what is called *crowding in* effect of public funding. The evidence in the literature about the *crowding out* or *crowding in* effect of public support at the firm level is diverse. For instance, Marino *et al.* (2016) found *crowding out* effects in French firms with high levels of subsidies. Huergo and Moreno (2017) cannot reject the null hypothesis of *crowding out* effects for large firms in the presence of subsidies and loans. They have a dataset for Spanish firms with information about loans and public subsidies for projects. A similar result is found by Lokshin and Mohnen (2012) and Wallsten (2000) in their studies, respectively, with data for the Netherlands and firms in the United States. They measure public support by tax incentives over R&D investments, and cannot reject for large firms the null hypothesis of *crowding out* effects. Almus and Czarnitzki (2003), using non-parametric methods for Eastern Germany firms, did not find *crowding out* effects of public support. In addition, Czarnitzki and Lopes-Bento (2012, 2013) found some evidence of *crowding out* in Belgium.

For Latin American countries, we found a few studies about the effects of public support. Busom and Ospina-Espin (2017) found a positive effect of public support on the R&D decision of Colombian firms. Aboal and Garda (2015) found for Uruguay that public support did not decrease the private expenditure in innovation, notwithstanding some firms did not increase their private investment with the public grants. Hall and Maffioli (2008), in one study for Argentina, Chile, Brazil and Panama, conclude that the *crowding out* effect in these countries is not clear.

Ecuador is a country which has not a long tradition and experience in the performance of private R&D and innovation investment activities. In Appendix C4.1 we show the importance of government finance to R&D activities in the whole Ecuadorian economy, as measured by the percentage of intramural R&D financed by different sources (see the final two columns in the Appendix C4.1 table). According to this information, since 2006 to 2014 the average percentage of public finance to intramural R&D activities in the country is 48.19%. In contrast, what Ecuadorian firms finance privately of intramural R&D in the country is on average 5.48% for the same period. The rest is financed by higher education, private non-profit organizations, the "rest of the world", or from non-specified sources. However, when we look at the second column in this table, where it is shown the percentage of total intramural R&D in the country that goes to the business enterprise sector, independently of the source of funds, this average is about 37.61%. Hence, the private investment in R&D of business enterprises in Ecuador shows some weaknesses. In this direction, Schwartz and

Guapatin (2014), in their study about the innovation national system in Ecuador, already mentioned some weaknesses of its structure such as: the scarce innovation by firms and the limited public support instruments to promote it. For example, in Appendix C4. 2, we can see the public investment in R&D projects from 2011 to 2015, that for the whole period amounts 87 million of US dollars. Ecuador has been trying to intensify its innovation policies to solve deficiencies in this respect, but there is not yet full evidence about effectiveness of this public effort. There is only one study for Ecuador (Fernández-Sastre and Martín-Mayoral, 2015), in which the authors evaluate some innovation related support programs (not including subsidies). They obtain that they can have positive effects on internal R&D and other related expenditures but an opposite effect on external R&D. They perform their study for the period 2009-2011. Their research, however, does not consider subsidies and does not distinguish which part of the chance in the firm's investment is privately funded and/or funded by the public sector.

In this study, we explore firms' innovative expenditure in Ecuador and its relationship with public support through public subsidies. One of the aims of this study is not only check whether subsidies increase the total firm's investment or effort in R&D and related innovation investments (intensive margin), but also find out whether the effect of public support evidences the presence of *crowding out* or *crowding in* on private investment. Additionally, a second aim is contributing to the increase of debate about innovation public funds effectiveness in developing countries, since most of studies are focussed on developed countries. In developing countries, where the availability of funds is many times restricted, this type of studies is relevant for policy makers to design better instruments to support innovation. Finally, we are also interested in getting threshold levels to public support that induce firms to perform

R&D activities (extensive margin effects of subsidies). For all these purposes, we rely on González *et al.* (2005) and Arqué-Castells and Mohnen (2015) analytical framework to illustrate how public subsidies affect optimal R&D decisions. We use the currently available two non-overlapping waves of the National Innovation Activities Survey 2013 and 2015 (NIAS) "*Encuesta Nacional de Actividades de Innovación*", which provides firm-level data information for the periods 2009-2011 and 2012-2014, respectively, for Ecuadorian firms, and that is quite similar in structure to European CIS data.

Our results are manifold. First, subsidy successful applicants seem to be firms with likely financial constraints to invest in R&D projects. Also, there seems to be a preference from public agencies to finance firms with certain technological sophistication and higher risk from export markets. However, public agencies are probably not only picking firms facing market failures, but also cherry picking quite established firms in terms of sales, market power and good business expectations. Second, we obtain that the higher the expected subsidy for a firm the more likely it is to perform R&D and the higher the optimal investment effort. Hence, firms' public subsidies to R&D in Ecuador increase the *total* firm's effort in R&D investment. However, results also indicate the presence of a partial *crowding out* effect of public funding as regards private investment. This means that private effort is smaller with the subsidy than it would have been without the subsidy. Third, with a subsidy no higher than 10%, about 91% of non-R&D performing firms will be induced to invest. Finally, subsidy withdrawal only affects a very little percentage of firms that would abandon performance of R&D (0.1%). This indicates that public funding is being directed to a high extent to firms that would have performed R&D even if there was not a subsidy.

This chapter is organized as follows. In Section 4.2 we present the data and some descriptives. In Section 4.3 we introduce our analytical framework. Section 4.4

moves on to the econometric modelling. Section 4.5 explains in detail empirical specifications and results from estimation. Section 4.6 is devoted to policy issues for valuating subsidy effects. Finally, Section 4.7 concludes.

4.2. Data and descriptives

We use the currently available two non-overlapping waves of the National Innovation Activities Survey 2013 and 2015 (NIAS) "*Encuesta Nacional de Actividades de Innovación*", which provides firm-level data information for the periods 2009-2011 and 2012-2014, respectively, for Ecuadorian firms. The last wave has been recently made available for researchers. This is a survey sponsored by the Ecuadorian National Statistics and Census Office ("*Instituto Nacional de Estadísticas y Censos*", INEC), and the Secretary of Superior Education, Science, Technology and Innovation ("*Secretaría de Educación Superior, Ciencia, Tecnología e Innovación*", SENESCYT). The NIAS provides information about firms' characteristics related to innovation activities following the Frascati Manual and the Oslo Manual Guide of the OECD (OECD, 2002; OECD and Eurostat, 2005). The information in the survey is similar in structure and variables to the Community Innovation Surveys (CIS) for European countries. The NIAS also includes other more general firms' characteristics such as sector of activity, sales and employment. In the first wave, the dataset has information for 2,815 firms. In the second wave information corresponds to 6,275 firms but, unfortunately, only 1,065 firms have been included in two waves of the survey. The remaining 6,960 firms have only data in one wave (1,750 firms in wave one and 5,210 firms in wave two). Hence, pooling information from both waves in the survey, our working sample amounts 9,090 observations corresponding to 8,025 different firms. In each wave, firms have been extracted from the population in the last Ecuadorian Economic Census (2010), that covers all regions in the country and is representative of industry-size strata. In the survey, NIAS includes firms operating in all sectors of the Ecuadorian economy, except agriculture, following the ISIC Rev. 4 classification from the United Nations. The survey also excludes firms with less than 10 employees. Answering the questionnaire is compulsory for firms.

In this chapter, we use a wide definition of R&D expenditures. Our definition includes not only internal and external R&D expenditure but also investments in other related activities to innovation that the survey lists under the heading of "Innovative efforts" and that includes: acquisition of machinery and equipment, acquisition of hardware, acquisition of software, acquisition of disembodied technology, consultancy and technical assistance, engineering and industrial design, workers training, and market research. In the survey questionnaire, these types of investments only include their part related to firms' innovation activities. For instance, replacement of a machine by another one of similar characteristics does not imply an innovation activity. The reason for using this wider definition of R&D/innovation expenditure is the way in which it is defined in the survey the government subsidy rate. In particular, it is defined as the percentage for each firm than during the three years' period of information for each wave represents the public funding over the *total* amount of investment in innovation (internal and external R&D plus other investment in innovation related activities).

From the total number of firms' observations in our working sample, in 169 cases firms indicate the presence of subsidies as a source of financing their R&D investments. Of these, 68 correspond to wave one and 101 to wave two. In addition, in 4,024 firms' observations, firms declare to be R&D performers. Of these, 1,409 correspond to wave one and 2,615 to wave two.

Next, we present some sample information about R&D expenditures and granted subsidies. The first column in Table C4.1 reports the percentage of firms engaged in

R&D each one of the three years contained in each wave of the survey. Hence, we have available information in this respect from 2009 to 2014. From now onwards, we call it R&D for simplicity, although we mean the before introduced wider definition of technological investments. According to this information, the yearly average probability for firms undertaking R&D in the periods covered by the first and the second wave of the survey is 38.11% and 28.76%, respectively. The second column in Table C4.1 shows the percentage of firms that along the first and second wave periods have subsidized technological investments. Public subsidies are not a commonly spread policy among Ecuadorian firms since about 2.41% and 1.61% of them receive subsidies in the first and second waves, respectively. However, if we look at subsidized firms (see the fourth column in Table C4.1) we notice that more than 35% of their technological investment has been financed by the subsidy.

Finally, the last four columns of Table C4.1 show the technological effort (technological investment over sales) of four different groups of firms: all firms, and the subgroups of firms with technological investment, firms with subsidy, and firms without subsidy. The average technological effort for firms with technological investment is around 8.22% and 5.30%, respectively, for waves 1 and 2 of the survey. For firms with subsidy, the average technological efforts are larger and are about 19.31% (in wave 1) and 8.60% (in wave 2). The results shown in columns 6, 7 and 8 of Table C4. 1 clearly uncover that the firms that get subsidies are the ones with the higher technological effort. This suggests a positive association between the granting of subsidies and the firms' wide R&D effort. However, without a proper econometric analysis, we cannot infer yet whether there is a crowding-in or crowding-out effect of subsidies over R&D effort, since this positive association at a descriptive level may just capture the effect of omitted variables affecting this relationship or reverse causality issues coming from the possibility of firms with more R&D effort being more likely to get subsidies or higher subsidies. As a final point, comparing wave 2 with wave 1 descriptive analysis as regards technological activity (technological effort and subsidies to technological investment), we notice that all percentages get reduced in the period 2012-2014 *versus* 2009-2011. This suggests both less extensive and intensive margins in the performance of technological investments and also a decrease in the intensive and extensive margins coverage of subsidies.

Table C4. 1 Innovation performance and Public support

			Public Support[a] (%)		Innovation effort[b] (%)			
Year	Firms with R&D wide activities (%)	Firms with Public support[a] (%)	All firms	Firms with P. Support	All firms	Firms with R&D wide activities	Firms with P.Support[a,c]	Firms without P.Support[a,c]
2009	35.49				2.95	8.44		
2010	38.51	2.41	0.96	39.91	3.20	8.31	19.31%	2.87%
2011	40.32				3.18	7.90		
2012	27.06				1.65	4.20		
2013	27.92	1.61	0.56	34.94	1.71	6.14	8.60%	1.57%
2014	31.31				1.74	5.56		

a: The information for these variables is only available at once for each wave but covers the three-years period in each wave.
b: Expenditure in internal and external R&D and innovation related activities over sales (wide definition of R&D expenditures).
c: The mean difference in innovation effort between firms with subsidy and firms without subsidy is for the first wave of the survey 16.43% (2009-2011) and for the second wave of the survey 7.03% (2012-2014), both differences significant at 1% level.

4.3. Analytical framework

In this section we rely on González *et al.* (2005) and Arqué-Castells and Mohnen (2015) analytical framework to illustrate how public subsidies affect optimal R&D decisions in the presence of setup costs of firms in two dimensions: the decision to perform R&D and how much to invest. Hence, the structural modelling displayed in this section will allow us, once moved into empirics, to discern whether and how much public subsidies to R&D affect the extensive and the intensive margins of the performance of firms' R&D activities in the Ecuadorian economy.

A given firm *i* should choose whether or not investing in R&D and how much. If it decides not investing in R&D, its profits are $\pi_{it}^{No\ RD}$. If it decides investing in R&D, it has to pay a variable investment $RD_{it} > 0$ and a setup cost $F_{it} > 0$. Assume that the public sector subsidizes a fraction ρ_{it} of total firm variable R&D expenditure.[52] The firm's expected profits from doing R&D are:

$$(1)\ \pi_{it}^{RD} = \exp\left(Z_{it}\theta + v_{it}\right) RD_{it}^{\phi} - \left(1-\rho_{it}\right) RD_{it} - F_{it}$$

where $\exp\left(Z_{it}\theta + v_{it}\right) RD_{it}^{\phi}$ is firm's revenue that depends on several components: i) $\exp\left(Z_{it}\theta + v_{it}\right)$ captures the productivity of R&D investments as a function of firm's observable characteristics Z_{it}, a vector of parameters θ, and a random R&D productivity shock v_{it} observed by the firm but not by the econometrician; and, ii) also firm's revenue depends on R&D expenditure itself with a lower (null) to higher intensity depending on the value of the parameter $\phi \in [0,\ 1)$, which reflects the elasticity of the firm's revenue to R&D.

The first order conditions (FOC) from (1) with respect to R&D give us the optimal R&D investment:

$$(2)\ RD_{it}^{optimal^*} = \left[\frac{\phi \exp\left(Z_{it}\theta + v_{it}\right)}{\left(1-\rho_{it}\right)}\right]^{\frac{1}{1-\phi}}$$

[52] We model subsidies as a share of to-be-incurred R&D expenditures.

Hence, introducing the level of optimal R&D expenditure into the profit function in (1) we get an expression for optimal profits:

$$(3)\ \ \pi_{it}^{RD} = \frac{1-\phi}{\phi}\left(1-\rho_{it}\right)^{\frac{\phi}{\phi-1}}\left(\phi\exp\left(Z_{it}\theta+v_{it}\right)\right)^{\frac{1}{1-\phi}} - F_{it}$$

Firm i performs R&D when the profits in (3) are greater than the profits of non-performing R&D, that is

$$(4)\ \ \frac{1-\phi}{\phi}\left(1-\rho_{it}\right)^{\frac{\phi}{\phi-1}}\left(\phi\exp\left(Z_{it}\theta+v_{it}\right)\right)^{\frac{1}{1-\phi}} > F_{it} + \pi_{it}^{No\ RD},$$

condition that if satisfied as one equality allows us isolating the fraction of total firm R&D that should be subsidized to make the firm indifferent between investing or not in R&D. We call this subsidy the threshold subsidy:

$$(5)\ \ \rho_{it}^{threshold} = 1-\phi^{\frac{\phi-1}{\phi}}\left(\phi\exp\left(Z_{it}\theta+v_{it}\right)\right)^{\frac{1}{\phi}}\left(\frac{1-\phi}{F_{it}+\pi_{it}^{No\ RD}}\right)^{\frac{1-\phi}{\phi}}$$

Substituting (5) into (2) we get an expression for the corresponding R&D threshold:

$$(6)\ \ RD_{it}^{threshold} = \left[\frac{F_{it}+\pi_{it}^{No\ RD}}{\left(1-\phi\right)\exp\left(Z_{it}\theta+v_{it}\right)}\right]^{\frac{1}{\phi}}$$

Therefore, one firm optimally invests in R&D when its optimal R&D according to (2) is higher than its threshold R&D in (6). It is very relevant to notice at this stage that the subsidy ρ_{it} affects the optimal R&D expenditure but not the threshold R&D expenditure. This will turn out to be very important for recovering the parameters of the threshold R&D equation in the empirical part of this chapter. It will allow identification.

4.4. Econometric modelling

4.4.1. The optimal and the threshold R&D efforts

In our empirical specification we are going to work with R&D efforts instead of with R&D level expenditures. The R&D effort is defined as the ratio of R&D level expenditures over firms' sales. We assume, similarly to González *et al.* (2005), that effort increases monotonically with the level of R&D expenditure for a given firm. Under this assumption, econometrically it is interchangeable in the empirical counterparts of expressions (2) and (6) the use of R&D effort instead of R&D level expenditure (as in González *et al.*, 2005).

Accordingly, let $rde_{it}^{optimal^*}$ and $rde_{it}^{threshold}$ denote the optimal and the threshold effort in R&D, respectively, already transformed taking logs. The optimal R&D effort will be observed only if $rde_{it}^{optimal^*} - rde_{it}^{threshold} > 0$. This decision choice and the subsequent observability of a firm R&D effort fits econometrically into a type-II Tobit framework (also known as sample selection model). This model is originally defined by the following two equations once taking logs to the left and right hand sides of expressions (2) and (6):

(7) $rde_{it}^{optimal^*} = -\beta \ln\left(1-\rho_{it}\right) + X_{1,it}\beta_1 + \varepsilon_{1,it}$

(8) $rde_{it}^{threshold} = X_{2,it}\beta_2 + \varepsilon_{2,it}$

where $\beta = \dfrac{1}{1-\phi}$, $\varepsilon_{1,it} = \dfrac{v_{it}}{1-\phi}$, and $\varepsilon_{2,it} = \dfrac{v_{it}}{\phi}$. Notice that the subsidy fraction ρ_{it} appears in the $rde_{it}^{optimal^*}$ equation in the same way it appears in the FOC in (2), and that

(7) incorporates the reduced form determinants of $\ln\phi$ and Z_{it} in the new vector of regressors $X_{1,it}$. Differently, the $rde_{it}^{threshold}$ equation, according to the model does not depend on the subsidy and, hence, it only has reduced form determinants for $\ln\left(F_{it}+\pi_{it}^{No\ RD}\right)$, $\ln(1-\phi)$ and Z_{it}. The model also provides possible natural exclusion restrictions in the $rde_{it}^{optimal^*}$ equation with respect to the $rde_{it}^{threshold}$ equation, since the vector of regressors $X_{2,it}$ in (8) includes proxies for $\ln\left(F_{it}+\pi_{it}^{No\ RD}\right)$ that do not necessarily appear in the vector $X_{1,it}$ (which includes reduced form determinants for ϕ and Z_{it}).[53]

But since the $rde_{it}^{threshold}$ is not observed in the data and instead we observe the $rde_{it}^{optimal^*}$ if $rde_{it}^{optimal^*}-rde_{it}^{threshold}>0$, there are two steps to follow to get values for the β_1 and β_2 parameter vector components. For the estimation of β_1 we combine the information in (7) and (8) to estimate the following standard type-II Tobit model that includes the level equation of interest for the $rde_{it}^{optimal^*}$ and its observability rule (the selection equation):

$$(9)\quad rde_{it}^{optimal}=\begin{cases} rde_{it}^{optimal^*}=-\beta\ln\left(1-\rho_{it}\right)+X_{1,it}\beta_1+\varepsilon_{1,it} & if\ d_{it}=1\\ =0 & if\ d_{it}=0\end{cases}$$

$$(10)\quad \begin{aligned} d_{it}&=1\left[rde_{it}^{optimal^*}-rde_{it}^{threshold}>0\right]\\ &=1\left[-\beta\ln\left(1-\rho_{it}\right)+X_{1,it}\beta_0^{no\_exc.rest}+X_{2,it}^{exc.rest}\beta_0^{exc.rest}+\varepsilon_{0,it}>0\right]\end{aligned}$$

[53] In fact, in our empirical specifications we will proxy for F_{it} and consider than $\pi_{it}^{No\ RD}$ is normalized to zero.

where $1[\cdot]$ is the indicator function that takes value 1 when it is true the condition that is in brackets and 0 otherwise, $\beta_0^{no\_exc.rest} = \left(\beta_1 - \beta_2^{no\_exc.rest}\right)$, $\beta_0^{exc.rest} = \left(0 - \beta_2^{exc.rest}\right)$, $\varepsilon_{0,it} = \left(\varepsilon_{1,it} - \varepsilon_{2,it}\right)$ and $rde_{it}^{optimal^*}$ and $rde_{it}^{threshold}$ are given by equations (7) and (8). The parameters in (9) and (10), β, β_1, $\beta_0^{no\_exc.rest}$ and $\beta_0^{exc.rest}$, can be estimated either by maximum likelihood or by the two-steps sample selection correction Heckman's model.[54] For estimation we assume $\varepsilon_{1,it}$ and $\varepsilon_{0,it}$ to follow a bivariate normal distribution, independent of $X_{2,it}$ ($X_{1,it}$ is a subset of $X_{2,it}$).

Differently, the parameters of the R&D effort threshold equation cannot be estimated since $rde_{it}^{threshold}$ is unobservable. But, fortunately, we can recover its value with the information about the estimated parameters in the $rde_{it}^{optimal^*}$ and the yes/no binary choice equations above. For uncovering threshold equation parameters, we also need another relevant piece of information in the model, that is that the parameter β associated to the subsidy variable ρ_{it} will be estimated twice. On the one hand, it will be estimated in the level equation of interest for the $rde_{it}^{optimal^*}$ in (9). On the other hand, it will be estimated in the *probit* model described by (10). This is crucial since we know that the parameters estimated from a standard discrete binary choice model, such as our *probit* model in (10), are only "identified up to scale", being the scale σ, the squared root of the variance of the error term in the *probit* equation, $\varepsilon_{0,it}$. This means that in this type of models there is no information about σ in the sample data so σ cannot be estimated. The parameter β or the parameter vectors $\beta_0^{no\_exc.rest}$ and $\beta_0^{exc.rest}$ in (10) are

[54] In the empirics in this chapter we perform the more efficient one-step estimation by maximum likelihood of the sample selection model.

not in absolute values estimated by the *probit* part of the model but instead what we estimate is $\beta^{scaled} = (\beta/\sigma)$, $\beta_0^{scaled\_no\_exc.rest} = \left(\beta_0^{no\_exc.rest}/\sigma\right)$ and $\beta_0^{scaled\_exc.rest} = \left(\beta_0^{exc.rest}/\sigma\right)$. However, since we can get our parameter of interest β free of scale, that is in absolute value, from the estimation of the linear regression equation for the $rde_{it}^{optimal^*}$ in (9), our theoretical framework allows us an estimate of σ that can be obtained isolating $\sigma = \beta/\beta^{scaled}$ from $\beta^{scaled} = (\beta/\sigma)$. Hence, the ratio of the parameter for the subsidy variable estimated in (9) over the one for the same variable estimated in (10) gives us an estimate of the standard deviation of $\varepsilon_{0,it}$. Why is this important to uncover all the unknown parameters in the R&D effort threshold equation (β_2 in (8))? Because now we can use the structure in the *probit* equation in (10), that is the relationships above about $\beta_0^{no\_exc.rest} = \left(\beta_1 - \beta_2^{no\_exc.rest}\right)$ and $\beta_0^{exc.rest} = \left(0 - \beta_2^{exc.rest}\right)$, to isolate the whole β_2. Since $\beta_0^{no\_exc.rest} = \sigma\beta_0^{scaled\_no\_exc.rest}$ and $\beta_0^{exc.rest} = \sigma\beta_0^{scaled\_exc.rest}$, and what we estimate with the *probit* model are the scaled versions of these parameters:

$$(11)\quad \begin{aligned} \hat{\beta}_2^{no\_exc.rest} &= \hat{\beta}_1 - \hat{\sigma}\hat{\beta}_0^{scaled\_no\_exc.rest} \\ \hat{\beta}_2^{exc.rest} &= 0 - \hat{\sigma}\hat{\beta}_0^{scaled\_exc.rest} \end{aligned}$$

where $\hat{\beta}_1$ comes from the estimation of the $rde_{it}^{optimal^*}$ equation and $\hat{\beta}_0^{scaled}$ comes from the estimation of the *probit* equation. Notice that the vector $\hat{\beta}_0^{scaled}$ has been divided into two vectors, one corresponding to the subgroup of variables in $X_{2,it}$ that is also included in $X_{1,it}$ ($\hat{\beta}_0^{scaled\_no\_exc.rest}$) and the other corresponding to the subgroup of variables in $X_{2,it}$ that is not included in $X_{1,it}$ ($\hat{\beta}_0^{scaled\_exc.rest}$).

It is important to notice that the relevant issues for identification of the parameters of the threshold equation (8) is that β is both present in the optimal R&D effort equation (9) and the selection equation (10), and that the subsidy share variable does not enter the threshold equation. All this guarantees that the standard error of $\varepsilon_{0,it}$ in (10), that is σ, can be recuperated from $\sigma = \beta / \beta^{scaled}$, which allows recovering all the parameters of the threshold equation through (11).

4.4.2. The expected subsidy share

In the estimation of equations (9) and (10) there are still two previous problems to deal with. On the one hand, there can be a non-random selection of subsidy beneficiaries. On the other hand, subsidies may suffer from endogeneity problems in the R&D equations if agencies selecting recipients take into account the R&D effort and the performance of firms. This will make "observed" subsidy shares to be correlated with R&D productivity shocks. To solve for both related problems, we consider, as in González *et al.* (2005) and Arqué-Castells and Mohnen (2015), that when firms decide whether to invest or not in R&D and how much to invest, they consider that some public support is possible and, hence, they consider for their decisions "expected" subsidies. For them, firms react to expected subsidy shares, which can be considered predetermined with respect to R&D productivity shocks. Therefore, previous to estimation of equations (9) and (10) we require estimation of "expected" subsidies (the ratio of R&D publicly financed) with value for all firms, not just for the ones with "actual" positive subsidy shares in the estimation sample.

Let ρ_{it}^{*} denote the firm's latent subsidy share, which is formally modelled as

(12) $\rho_{it}^{*} = \gamma_1^{'} w_{1,it} + u_{1,it}$

where $\gamma_1^{'}$ captures the effects of explanatory variables on the potential firm's subsidy share and $u_{1,it}$ denotes idiosyncratic errors that affect ρ_{it}^{*}. The observed counterpart to ρ_{it}^{*} is defined as

(13) $\rho_{it} = \mathbf{1}\left[d_{\rho,it}^{*} > 0\right]\rho_{it}^{*} \equiv d_{\rho,it} \cdot \rho_{it}^{*},$

where $\mathbf{1}[\ ]$ again denotes the indicator function taking the value one if the condition between squared brackets is satisfied, and zero otherwise. This notation reflects that the subsidy share of firm *i* is observed to be positive only if firm *i* holds a subsidy, that is if $d_{\rho,it} = 1$ or what is equivalent, $d_{\rho,it}^{*} > 0$, where $d_{\rho,it}^{*}$ denotes a latent variable underlying firm *i's* propensity to hold a subsidy given firm and structural characteristics $w_{2,it}$, and $d_{\rho,it}$ is the observed dichotomous variable with 0/1 value that determines whether or not the firm actually has a subsidy . Formally,

(14) $$\begin{aligned} d_{\rho,it}^{*} &= \gamma_2^{'} w_{2,it} + u_{2,it} \\ d_{\rho,it} &= \mathbf{1}\left[d_{\rho,it}^{*} > 0\right], \end{aligned}$$

where $\gamma_2^{'}$ captures the effects of explanatory variables on the propensity to have a subsidy and $u_{2,it}$ denotes idiosyncratic errors that affect $d_{\rho,it}^{*}$. $\mathbf{1}[\ ]$ denotes the indicator function taking the value one if the condition between squared brackets is satisfied, and zero otherwise. Since in our data we do not have individualized information on subsidies about the application stage by firms and the granting stage by agencies, but only the information about firms holding a subsidy or not, in the probability equation characterizing subsidy holders against non-holders, explanatory variables will capture the firm's likelihood of application and/or the agency's suitability rules.

We assume that the error terms $u_{1,it}$ and $u_{2,it}$ follow a bivariate normal distribution. Hence, in estimation we allow for correlation of these two idiosyncratic error terms. The observed subsidy share ρ_{it} is treated as a censored variable and its "expected" counterpart ρ_{it}^{*} is estimated through a Tobit-type II model (Heckman's sample selection model). This procedure corrects for non-random selection of subsidy beneficiaries when estimating the "expected" subsidy share ρ_{it}^{*}. This allows for consistent estimation of parameters in the subsidy equation that can be extrapolated to all the sample and not only to the subsample of firms that hold a subsidy (Heckman, 1979). This is a suitable method with our data since there are many firms in our sample without a subsidy. The implemented method will allow testing for the presence of sample selection in the estimation of the subsidy equation. The explanatory variables in $w_{1,it}$ are also included in $w_{2,it}$.

4.5. Empirical specification and results

In this chapter we obtain the parameters of five equations: 1) The yes/no subsidy equation in (14) with parameters $\gamma_{2}^{'}$; 2) the "expected" subsidy equation in (12) with parameters $\gamma_{1}^{'}$; 3) the selection equation yes/no R&D performance in (10), with parameters β, $\beta_{0}^{no\_exc.rest}$ and $\beta_{0}^{exc.rest}$, for observability of the firm's optimal R&D effort equation in (9); 4) the firm's optimal R&D effort equation in (9) with parameters β and β_{1}; and, finally, 5) the threshold equation in (8) with parameters β_{2}. In what follows, we comment on the empirical specification of the different equations as regards explanatory variables and some exclusion restrictions, and present the corresponding results from estimation of each equation.

4.5.1. Public support: Expected subsidy share and yes/no subsidy equations

The vector of explanatory variables for the likelihood of getting a subsidy should include variables explaining firms' willingness to apply and/or the eligibility rules by the agency. Our vector of variables in $w_{2,it}$ in (14) has been selected on the basis of previous empirical literature on this topic (see, for instance, González *et al.*, 2005, Arqué-Castells and Mohnen, 2015, Busom *et al.*, 2014, and Busom *et al.*, 2017). This set of regressors is assumed to be predetermined to R&D productivity shocks in period *t* (the same assumption than in González *et al.*, 2005), to guarantee afterwards that the estimated "expected" subsidy share by the Heckman's (1979) method is uncorrelated with the idiosyncratic error terms of both the optimal R&D effort equation and its corresponding selection equation. Since a year *t* wave of the survey incorporates information for some variables in periods *t*, *t-1* and *t-2*, to work in favour of predeterminedness of regressors, when it is possible we include them lagged two periods, that is in period *t-2*.[55] We do this for variables such as firms' size (as measured by the log number of employees), a dummy variable indicating whether the firm is an exporter, the log export intensity (defined over sales), the market share of the firm in the industry (for capturing market power), a dummy variable indicating whether the firm invests in fixed capital (as a proxy for capital growth and, more importantly, for demand expectations), and a ratio of the firm's log labour productivity over the mean log labour productivity of its sector (the productivity measures are calculated as sales per employee and the sectoral mean is calculated at the 3-digits sector level according to the ISIC Rev. 4 classification). The firm's labour productivity relative to the industry average captures the distance to the technological frontier and also may capture that returns to innovation may be higher for more productive firms. For other variables we do not have

[55] Results do not vary if instead we use the lag *t-1*.

information in the survey for periods *t-1* or *t-2*, but only for period *t*. This is the case for a dummy variable denoting whether the firm has foreign capital, a dummy variable indicating whether the firm belongs to a business group, and a dummy variable that takes into account whether the firm has a formal department of Information and Communication Technologies (ICT). Firms with foreign capital and/or firms belonging to a business group could have higher propensity to finance R&D investments with the internal capital market of the group they belong to, rather than through public subsidies. Furthermore, highly productive firms on a sector are also less financially constrained to invest in R&D projects and, hence, they need less public support. Additionally, dummies classifying firms' sectors in low tech, med-low tech, med-high tech, and high tech for manufacturing, and in knowledge intensive sectors or non-knowledge intensive sectors for services, following the OECD classification as regards knowledge intensity, are included. Finally, a geographical dummy for firms in Guayas, Pichincha or Azuay provinces, plus a time dummy for observations corresponding to the second wave of the survey, are also included. Notice that only the three mentioned provinces account for 64.27% of firms in Ecuador. Variables such as ICT, or even the technological classification of sectors, might be capturing the firm's degree of technological sophistication and the quality of submitted projects, some things that likely agencies consider for eligibility.

In summary, we have included some firms' characteristics and some firms' variables which can be related to the likelihood of getting a subsidy.

The vector of regressors in $w_{1,it}$ for the latent "expected" subsidy share equation in (12) is the same than the vector $w_{2,it}$ for the likelihood of getting a subsidy in (14) but with some little changes. In particular, in the equation for the fraction of public support we reduce to three the industry technological classification dummies: one for

Manufacturing "High" (that aggregates med-high and high tech manufacturing sectors), one for "knowledge intensive" Services, and another one for Other sectors. The dependent variable for estimation in the subsidy share equation is $log\,\rho_{it}$ for the subsample of firms with subsidy.

A further description of all the variables employed in this study can be found in the Appendices C4. 3 and C4. 4, with description of variables and summary statistics.

Results for the expected subsidy share and yes/no subsidy equations

In Table C4.2 we show the results from the joint estimation by maximum likelihood of the yes/no subsidy equation (column 1) and the "expected" subsidy equation (column 2) according to the Type-II Tobit model. At the bottom of the table, the performance of a Wald test of independent equations (correlation between the two equations being equal to zero) confirms rejection of the null of this test and, hence, supports the joint estimation through a sample selection model that corrects for sample selection when estimating the expected subsidy equation with the subsample of firms' observations holding a subsidy (a total of 169 observations).

Table C4. 2 Public Support estimation: *Heckman* Model (Type-II Tobit)

VARIABLES	(1) *d*_Subsidy (Yes/No)	(2) *Log* Subsidy share
Size *t-2*	0.10***	-0.42
	(0.03)	(0.37)
*d*_ICT	0.28***	2.81***
	(0.08)	(1.06)
Export intensity *t-2*	0.06*	-0.14
	(0.04)	(0.51)
*d*_export *t-2*	0.18	0.87
	(0.13)	(1.62)
*d*_foreign	-0.38**	-1.49
	(0.15)	(1.83)
*d*_group	-0.26**	-1.57
	(0.11)	(1.17)
Market share *t-2*	0.61*	0.61
	(0.35)	(5.11)
*d*_fixed investment *t-2*	0.39***	2.77***
	(0.08)	(1.06)
*d*_geographical $_{\text{Guayas, Pichincha, Azuay}}$	-0.17**	2.27**
	(0.07)	(0.95)
*d*_time $_{\text{second wave of the survey}}$	-0.13*	-2.28***
	(0.07)	(0.85)
Relative productivity *t-2*	-0.45***	-0.81
	(0.16)	(2.22)
Med-Low tech manufacturing	0.28**	
	(0.11)	
Med-High tech manufacturing	0.19	
	(0.17)	
High tech manufacturing	0.52**	
	(0.25)	
Med-High & High tech manufacturing		2.81**
		(1.14)
Knowledge intensive services	-0.28***	0.22
	(0.10)	(1.20)
Other sectors	0.44***	0.39
	(0.09)	(1.16)
Constant	-2.17***	-11.07***
	(0.17)	(3.94)
Observations	9,090	169

Note:

1. Robust standard errors in parenthesis; *** p<0.01, ** p<0.05, * p<0.1.
2. Rho=0.54; Wald test of independent equations (Rho=0): $Chi^2(1) = 9.90$ and p-value=0.0017.
3. Log pseudolikelihood = -1259.039.
4. In column (1) the reference category for the technological classification of sectors is the aggregated category of Low tech manufacturing plus non-Knowledge intensive services. In column (2) it is the aggregated category of Low & Med-Low tech manufacturing plus non-Knowledge intensive services.

As expected, more variables are statistically relevant in determining the likelihood of successfully getting a subsidy than they are in the explanation of the firm's expected subsidy share. This is quite common in related literature on this topic.

In the yes/no subsidy equation, there is a group of variables probably capturing the firm's lack of financial constraints to invest in R&D projects, such as the existence of foreign capital, the firm belonging to a business group and the relative productivity as regards the mean of the sector, which render a negative and statistically significant sign in estimation, corroborating our expected results for these variables. Also firms located in the three provinces of the country with higher concentration of economic activity have a lower likelihood to have a subsidy. The time period that corresponds to the second wave in the survey is also associated to a lower likelihood of having a subsidy. Differently, some other variables justify a higher likelihood for the firm having a subsidy. These are the variables firms' size, the dummy for the use of ICT, export intensity, market share and capital growth. It can be that technological sophistication (ICT) and higher risk associated to export markets encourages public agencies to provide subsidies. As for size, it could be that only firms with a given size are able to go through the administrative process to apply for a subsidy.[56] There can also be a tendency of public agencies to provide subsidies to large firms, with high market share and with expectations of demand growth (as proxy by the investment in fixed capital). If this was the case, agencies could be blamed for not picking firms subject to market failures for the performance of R&D activities but cherry picking quite established firms in terms of sales, market power and good business expectations.

As for the subsidy equation, the relevant variables that affect positively the subsidized fraction of R&D are the firm's use of ICT, the firm's investment in fixed

[56] Sometimes the access to public finance requires a lot of administrative work and documents to fill.

capital (a proxy for capital growth and the firm's demand expectations), whether firms belong to the group of Med high and High tech manufacturing firms, or to the three core provinces for economic activity. Again, the second wave of the survey explains lower subsidy shares. As the dependent variable in this equation is in the log form and the statistically significant regressors are dummy variables, the estimated parameters have the interpretation of semi-elasticities. Estimated semi-elasticities are economically relevant since, for instance, their values for variables such as the firm's use of ICT and the firm investing in fixed capital, indicate that if a firm not performing one of these activities performs one of them it could enjoy an increase of the subsidy share by about 280%.

4.5.2. Optimal R&D effort equation

The optimal R&D effort equation in (9) depends on the "expected" subsidy share through the regressor $-\ln\left(1-\rho_{it}^{*}\right)$ and on the vector of regressors $X_{1,it}$. This vector of regressors includes variables assumed to be exogenous or predetermined variables that proxy for several types of elasticities involved when judging how profitable is for the firm to expend a given amount of money in R&D. In addition, we also include two dummy variables, *d_foreign* and *d_group*, which take value 1 whenever the firm has foreign capital participation and belongs to a business group, respectively. The two variables try to capture the possibility of firms' access to an internal capital market that allows better financing of innovation activities and, hence, alleviates potential firms' financial or liquidity constraints. Furthermore, we will also include in this vector of regressors, some controls in estimation such as the variables of firms' size (as measured by the log number of employees), *log*(age), a geographical dummy for firms in Guayas, Pichincha or Azuay provinces, and a time dummy for observations corresponding to the second wave of the survey.

We aim at proxy for the elasticity of demand with respect to R&D, which is expected to be positive and, therefore, to have a positive impact on the optimal R&D effort of the firm, and the elasticity of demand to prices, which is expected to be negative and, hence, to increase competition, which may decrease the optimal R&D effort of the firm. Additionally, the elasticity of demand with respect to R&D can be expressed as the elasticity of demand with respect to innovation (which has to do with demand conditions) times the elasticity of innovation with respect to R&D (which has to do with technological opportunities).

Among the variables to proxy for the firms' expected demand response to innovation, we have included four variables. The first one, *unsatisfied demand*, is constructed as the ratio of innovative firms in your sector-wave of the survey that declare as reason for performing activities directed to innovation, the detection of an unsatisfied demand in the product market. The second one, *quality improvement*, is more complex in construction and relies on a different type of question in the survey. Firms separately rank the relevance of a group of objectives for developing innovation activities (from less relevant to more, that is from a value of 1 to a value of 4, since we recode these values in the opposite direction they appear in the survey). We calculate the mean value from 1 to 4 that a given firm gives to all the objectives in the group. Then, we calculate the ratio of the rank from 1 to 4 the firm gives to the specific objective of improving the quality of products (included in the group) over the previous calculated average for all objectives. With this we have a measure of the *relative* importance for the firm of this particular objective for innovation. Next, to have a measure of the relative importance of this objective in general for the firm's sector and specific wave of the survey, we sum in a sector-wave all the calculated firms' ratios and normalize this measure by dividing by the total number of innovative firms in the particular sector-wave. The higher the value of this indicator, the more relative importance for a sector in a particular wave of the survey the objective of improving the quality of products when pursuing innovation. The third variable we consider, *d_fixed_investment*, is a dummy variable indicating whether or not the firm has invested in fixed capital. This type of investment can be considered a proxy for positive demand expectations (Busom *et al.* 2014). The fourth variable, *environmental concern*, is constructed with the same procedure applied to the construction of the variable *quality improvement*, and it will indicate the relative importance of the objective for innovation activities of the reduction of environmental damages for a specific sector and wave. We expect these four variables to have a positive effect on the firm' optimal R&D effort, since the existence of an unsatisfied demand in the market, to perceive that is relevant the improvement of the quality of products to be sold in the market and the existence of good expectations about demand conditions, as well as if the perception of environmental issues is relevant for consumers (it is of social interest), can generate incentives to innovate as it is expected the firm's demand to react positively to innovation.

As for the variables to proxy for the firms' innovation response to the expenditure on innovation activities (our broader definition of R&D), we construct two variables and also control for the OECD technological classification of sectors as regards technological intensity with dummy variables. The three types of variables are meant to proxy for the firms' technological opportunities succeeding in obtaining innovation outputs when they invest in R&D. The first one, *scientific-technical* *opportunities*, is constructed as the ratio of innovative firms in your sector-wave of the survey that declare as reason for performing activities directed towards innovation, the possibility of exploitation of ideas and/or scientific and technical novelties. The second one, *lack of technological information*, is constructed with the same procedure than the variable *quality improvement* but with the information of a question in the survey about obstacles to innovation. Firms separately rank the relevance of a group of obstacles to the performance of innovation activities (from less relevant to more, that is from a value of 1 to a value of 4, since we recode these values in the opposite direction they appear in the survey). We calculate the mean value from 1 to 4 that a given firm gives to all the obstacles in the group. Then, we calculate the ratio of the rank from 1 to 4 the firm gives to the specific obstacle of problems in getting information about technology (included in the group) over the previous calculated average for all obstacles. With this we have a measure of the *relative* importance for the firm of this particular obstacle to innovation. Next, to have a measure of the relative importance of this obstacle for the firm's sector and specific wave of the survey, we sum in a sector-wave all the calculated firms' ratios and normalize this measure by dividing by the total number of innovative firms in the particular sector-wave. The higher the value of this indicator, the more relative importance for a sector in a particular wave of the survey the obstacle of lack of knowledge and information about technology.

Next, we move on to the proxies for competition and market power. In this group we include four types of variables. The first one is *prices by demand and discounts*. This is a dummy variable with value 1 when the firm has introduced for the first time new methods for setting prices such as varying prices depending on the level of demand or discount systems to customers. This change in the system to set prices may obey to the firm facing an increase in competition in its product market. The second one is the variable *market share*, calculated as the ratio of firm's sales over total sales of the sector in a particular wave. It is typically considered that firms with higher market share face lower competition. The third group of variables includes both a dummy to account whether the firm exports or not (*d_export*) and its corresponding *export intensity* (as measured by the log of exports over sales). If export markets are more competitive, exporters will face higher competition. The final variable included is the expenditure in marketing innovations, as measured by the log of marketing innovative expenditures over sales (*new marketing intensity*). These investments may cover, for instance, a new type of advertising campaign, new brand image, the introduction of customer loyalty cards, new positioning of the product in the market, etc. This strategy of the firm may obey to a reaction of higher competition in the product market but also can generate a better position of the firm's products and, hence, reduce the competition the firm faces.

4.5.3. Observability rule (the selection equation) for the optimal R&D effort equation: The yes/no decision

The explanatory variables in equation (10) include the same explanatory variables than equation (9) plus a few variables more that are excluded from (9) and that can be then considered as exclusion restrictions contributing to better identification of the parameters in the optimal R&D effort equation. These extra variables are meant to proxy for set-up costs of innovative activities determining the firm's decision about whether performing or not R&D but not influencing the firm's decision about the R&D effort. These extra variables appear in the yes/no R&D decision since they exist in the threshold R&D effort equation (which is affected by set-up costs F_{it}). These can be variables related to the firm's technological sophistication and the employment of highly skilled workers. For the first, we use a dummy variable with value 1 when the firm utilizes ICT department (*d_ICT*). For the second, a dummy variable with value 1 when the firm has employees with a PhD, Master or university degrees (*d_skill*). Better human capital is expected to be related to a higher ability to generate ideas and quality R&D projects. Additionally, we also include two types of variables which may be relevant for the firm deciding to perform R&D and being able to overcome set-up costs. The first one, *d_protection*, is a dummy variable with value 1 when the firm uses at least one of the types of protection mechanisms considered in the survey (brand names, patents, utility models, industrial design, author's copyrights, designations of origin, confidentiality clauses for workers, or confidentiality contracts with suppliers and customers). This might be indicative of appropriability and protection of ideas and innovation outputs that encourages the performance of R&D. The second one is the variable related to productivity already used in the subsidy equations, and its square. This variable was constructed as the ratio of the firm's log labour productivity over the mean log labour productivity of its sector in a given wave of the survey. This variable may capture not only that more productive firms are abler to overcome set-up costs but also that returns to the performance of R&D activities may be higher for more productive firms. However, this variable may be also capturing, for firms with high productivity in a sector, that the projects they pursue are more ambitious and radical. If this was the case, this type of high productive firms could be facing higher set-up costs.

Besides theoretical considerations about these variables mainly explaining the R&D decision and not the optimal R&D effort, we have experimented with their inclusion also in the optimal R&D effort equation and confirmed that they were not statistically significant in this equation.

Results for the yes/no R&D decision and the optimal and threshold R&D effort equations

In Table C4.3 we show the results from the joint estimation by maximum likelihood of the yes/no R&D equation (column 2) and the optimal R&D effort equation (column 1) according to the corresponding Type-II Tobit model (Heckman's sample selection model). At the bottom of the table, the performance of a Wald test of independent equations (correlation between the two equations being equal to zero) confirms rejection of the null of this test and, hence, supports the joint estimation through a sample selection model that corrects for sample selection when estimating the optimal R&D effort equation with the subsample of firms' observations investing in R&D (4,024 from a total of 9,090 in the probit part). In column 3, Table C4.3 shows the recovered parameters of the model R&D effort threshold equation that are obtained by applying the transformation in (11) to the parameters in columns 1 and 2 in this table (that is $\beta_2 = \beta_1 - \sigma\beta_0$, making $\beta_1 = 0$ for the variables acting as exclusion restrictions in column 1).

Table C4. 3 The effect of public funding on R&D decision

	(1) (log of) Optimal R&D effort $\beta,\ \beta_1$	(2) *d*_R&D (Yes/No) $\beta^{scaled} = (\beta/\sigma),\ \beta_0$	(3) (log of) R&D effort threshold β_2
$-\ln(1-\rho_{it}^{*})$	0.159*	10.504*	
	(0.085)	(5.754)	
To proxy elasticity of demand w.r.t. innovation (demand conditions)			
Unsatisfied demand	0.029	0.217**	0.026
	(0.175)	(0.087)	(0.175)
Quality improvement	0.062	0.276***	0.057
	(0.240)	(0.096)	(0.239)
*d*_fixed investment *t-2*	0.203*	0.875***	0.189*
	(0.112)	(0.030)	(0.112)
Environmental concern	0.825***	0.418***	0.818***
	(0.217)	(0.101)	(0.217)
To proxy elasticity of innovation w.r.t. R&D (technological opportunities)			
Scientific-technical opportunities	0.519***	-0.042	0.519***
	(0.178)	(0.090)	(0.178)
Lack of technological information	-0.553**	-0.019	-0.552**
	(0.256)	(0.114)	(0.256)
Med-Low tech manufacturing	0.064	0.059	0.063
	(0.096)	(0.055)	(0.096)
Med-High tech manufacturing	-0.239*	0.155*	-0.240*
	(0.143)	(0.080)	(0.143)
High tech manufacturing	0.258	0.144	0.256
	(0.229)	(0.180)	(0.266)
Knowledge intensive services	-0.700***	-0.440***	-0.693***
	(0.092)	(0.037)	(0.092)
Other sectors	0.287**	-0.269***	0.291**
	(0.119)	(0.054)	(0.119)
To proxy elasticity of demand w.r.t. prices (competition and market power)			
Prices by demand and discounts	0.401***	0.263***	0.397***
	(0.110)	(0.076)	(0.110)
Market share *t-2*	-1.765***	0.417	-1.771***
	(0.594)	(0.299)	0.595
Export intensity *t-2*	-0.011	-0.036*	-0.010
	(0.036)	(0.021)	0.361
*d*_export *t-2*	-0.125	-0.076	-0.124
	(0.135)	(0.066)	(0.135)

	(1) (log of) Optimal R&D effort $\beta,\ \beta_1$	(2) d_R&D (Yes/No) $\beta^{scaled}=(\beta/\sigma),\ \beta_0$	(3) (log of) R&D effort threshold β_2
(novel) Marketing intensity *t-2*	0.074***	-0.055***	0.075***
	(0.011)	(0.006)	(0.115)
Controls			
*d*_foreign	-0.116	0.045	-0.116
	(0.105)	(0.054)	(0.105)
*d*_group	-0.019	-0.013	-0.018
	(0.086)	(0.044)	(0.086)
Size *t-2*	-0.216***	0.025*	0.216***
	(0.027)	(0.015)	(0.027)
Age	-0.123***	-0.010	-0.122***
	(0.043)	(0.021)	(0.042)
*d*_geographical $_{\text{Guayas, Pichincha, Azuay}}$	0.008	-0.167***	0.010
	(0.068)	(0.034)	(0.682)
*d*_time $_{\text{second wave of the survey}}$	-0.546***	-0.259***	-0.541***
	(0.069)	(0.036)	(0.069)
Exclusion restrictions			
*d*_skill		0.181***	-0.002***
		(0.055)	(0.000)
*d*_protection		0.761***	-0.011***
		(0.035)	(0.000)
*d*_ICT		0.213***	-0.003***
		(0.036)	(0.000)
Relative productivity *t-2*		0.252	-0.003
		(0.207)	(0.003)
(Relative productivity *t-2*)^2		-0.448***	0.006***
		(0.145)	(0.002)
Constant	-2.684***	-1.280***	-2.664
	(0.579)	(0.192)	(0.579)
Observations	4,024	9,090	9,090

Notes:

1. $(\beta,\ \beta_1)$, $(\beta^{scaled}=(\beta/\sigma),\ \beta_0)$ and β_2 refer to the parameters of equations (9), (10) and (8) respectively. The coefficients of the threshold equation have been calculated as $\beta_2=\beta_1-\sigma\beta_0$ (see (11) in the main text), making $\beta_1=0$ for the variables acting as exclusion restrictions.
2. Robust standard errors in parenthesis; *** p<0.01, ** p<0.05, * p<0.1. The standard errors of the threshold equation have been calculated according to the delta method.
3. Rho= -0.51; Wald test of independent equations (Rho=0): Chi^2(1) =35.49 and p-value=0.0000.
4. Log pseudolikelihood = -12891.83.
5. The expected support is introduced by the model regressor $-\ln(1-expected\ support)$, where the expected support comes from the prediction from the Heckman model.

The results in Table C4.3 indicate that both in the yes/no R&D decision and the optimal R&D effort equation, the higher the "expected" subsidy for a firm the higher the likelihood to perform R&D and the higher the R&D effort. For the 4 variables that proxy for the elasticity of demand with respect to innovation (demand conditions), we obtain that all of them are statistically significant and have the expected positive sign in the decision to perform R&D. In the R&D effort equation they have still the expected positive sign but only two of them are statistically significant (the existence of good expectations about demand conditions, as proxy by the firm investing in fixed capital, and the firm perception about innovations driven by environmental concerns to have positive effects on demand). Overall, results indicate that better demand prospects and higher sensibility of consumers to firms' innovation, encourage the performance of R&D and greater efforts in terms of R&D investments. This consumers expected response to innovation is captured by the existence in the firm's market of an unsatisfied demand (which innovation may cover), the existence of a perception in the firm's market about the relevance of improving products quality, good prospects for the firm's expansion materialized in the investment in fixed capital and, finally, the positive perception in the firm's market about questions of social interest such as whether innovations can help improving the environment. All this can signal that if the firm innovates, the firm's demand will respond positively to the innovations.

As regards the main variables which proxy for the elasticity of innovation with respect to R&D investments, they are not statistically significant in the decision to perform or not R&D, but they are statistically significant and with the expected signs in the optimal R&D effort equation. Hence, we obtain that if in the firm's market firms believe that there is a relevant possibility to exploit new ideas and/or new scientific and technical opportunities, the firm will increase its R&D effort. In addition, we also obtain that if in the firm's market firms think that one important obstacle for innovation is the lack or difficulty of access to technological information, the firm will decrease its R&D effort.

We obtain the following results for the variables that proxy demand elasticity with respect to prices (that is for competition and market power). The variable market share, although non-significant in the R&D yes/no decision, has a negative sign and high significance in the optimal effort R&D equation, indicating that market power discourages firms' R&D efforts. If a firm's change in the system to set prices towards a system in which prices adapt more to demand and can be associated with discounts to consumers is understood as indication of hither competition in the firm's market, then the positive sign we obtain for this variable both in the yes/no R&D and in the R&D effort equations, may suggest that more competition creates incentives for the performance of R&D activities ("scape competition effect", Arrow, 1962). The implementation of new marketing campaigns and the firm's export intensity render negative and statistically significant effects over the firm's decision to perform R&D. This may suggest that these firm's strategies are more substitutes than complements to the R&D activity. However, once performing R&D, the introduction of novelties in marketing that increase the intensity over sales of this activity, simultaneously increase the firm's R&D effort. The marketing campaign can be simply a reaction to higher competition in the product market and, hence, its positive effect on R&D effort may obey also to the before mentioned Arrow (1962) "scape competition effect".

Among controls, larger firms are more likely to perform R&D, but with a lower effort. Also older firms reduce the effort. In addition, observations from the second wave of the survey have both associated a lower propensity to perform R&D and a lower R&D effort. Finally, firms in Guayas, Pichincha and Azuay *per se* show a lower likelihood to perform R&D.

The results for the exclusion restriction variables that appear in column 2 but not in column 1 of Table C4. 3 are going to be commented with the results of the final column in this table, column 3, where results for the R&D effort threshold equation are presented. Notice that such variables appear in the yes/no R&D decision equation in expression (10) just because they are included among regressors of the threshold equation in our model, since they are excluded in the optimal R&D effort equation. In the threshold equation, as written in expression (6), these variables try to capture set-up costs in the performance of R&D activities. In this respect, we find that according to results in column 3 for these variables, firms located at a certain level of high relative productivity as regards the mean productivity of its sector are associated to higher set-up costs for innovation activities (likely because they pursuit more ambitious and radical R&D projects) and, hence, both to higher R&D effort thresholds and consequently a lower probability to perform R&D (see the decision rule in expression (10)). However, variables such as the availability in the firm of skilled labour, the existence in the firm of an ICT department, and if the firm uses any mechanism to protect ideas and innovation outputs, seem to alleviate set-up costs of innovative activities and/or the capacity to overcome them and, hence, to decrease R&D effort thresholds and consequently increase the likelihood of performing R&D activities.

As for the other variables in the threshold equation in column 3 but also included both in the optimal effort R&D equation in column 1 and in the yes/no R&D decision in column 2, we get as a general result that the same variables that are statistically relevant in explaining optimal R&D efforts are the ones that are also statistically relevant to explain R&D effort thresholds, and also with the same signs. It is also interesting to highlight that the threshold equation coefficients β_2 are quite close in magnitude to the coefficients β_1 in the optimal R&D effort equation (for the common variables in both equations). This is the consequence of a small value of σ (the standard deviation of the error term $\varepsilon_{0,it}$ in the *probit* equation for the yes/no R&D decision). As $\sigma = 0.014$, when we calculate $\beta_2 = \beta_1 - \sigma\beta_0$ the effect of β_0 is softened. The estimate of σ is obtained as $\sigma = \beta / \beta^{scaled}$, where β and β^{scaled} are, respectively, the estimated coefficients for the variable $-\ln\left(1-\rho_{it}^{*}\right)$ that appears as regressor both in the optimal R&D effort equation (column 1) and in the yes/no R&D decision (column 2).

4.6. Profitability gaps and subsidy effects

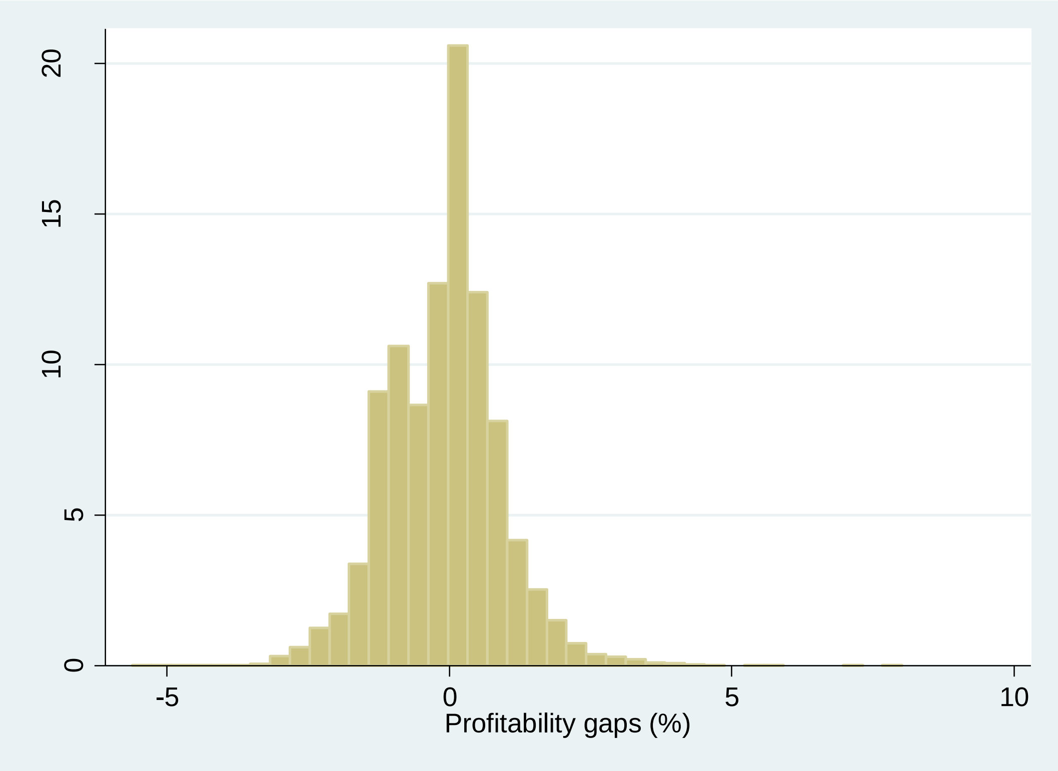
Now that we have already estimated optimal and threshold R&D effort equations, we can evaluate the effects of subsidies. Not only subsidies may induce firms to perform R&D, acting on the extensive margin by expanding the base of R&D performers, but also may increase R&D effort of R&D performers, acting on the intensive margin. From a policy point of view, we are interested in the evaluation of these issues.

According to the model predictions, and just to have a flavour about the percentage of firms that in the absence of subsidy would have not invested in R&D (since their profits would have been negative), we compute firms' individual optimal nonzero R&D efforts in the absence of subsidies $\left(\rho_{it}^{*} = 0\right)$ and calculate the difference with the predicted R&D effort thresholds. These differences are called "profitability gaps" and are calculated as:

(15) $Prof.\ GAP_{it} = \exp\left(X_{1,it}\beta_1\right) - \exp\left(X_{2,it}\beta_2\right)$

evaluated at mean zero of error terms $\varepsilon_{1,it}$ and $\varepsilon_{2,it}$ in equations (7) and (8), where arguments are exponentiated to obtain profitability gaps that are not under the log transformation. Firms with positive profitability gaps are the ones that the model predicts as performers of R&D activities even without the subsidy. Differently, firms with negative profitability gaps are the ones that at least without the subsidy are not expected to perform R&D. Calculating (15) for all of our sample observations, we get that in 55.52% of observations profitability gaps without subsidy are negative. The absolute value of the negative gaps mean is about 0.76 and the mean of positive gaps is about 0.73. Figure C4. 1 graphs the distribution of the estimated profitability gaps.

Figure C4. 1 Profitability gaps distribution



4.6.1. Inducement effects of subsidies (extensive margin)

"Trigger subsidies" (subsidies required to engage in R&D)

For firms (55.48%) that even with the currently expected subsidy they have a negative profitability gap (defining now profitability gaps as in (15) but taking into account the expected subsidy effect on the optimal R&D effort equation), we can calculate the "trigger subsidy", that is the value of ρ_{it}^{*} that will induce them, however, to invest in

R&D. This is nothing more than the corresponding value that makes 0 their negative profitability gaps:

$$(16)\quad -\beta \ln\left(1-\rho_{it}^{*}\right)+X_{2,it}\left(\beta_{1}-\beta_{2}\right)=0$$

For all these firms, classified as non-performers, Table C4.4 reports the distribution of trigger subsidies. The estimated trigger subsidies are such as with an expected subsidy of less than 1% of R&D expenses, 31.23% of nonperforming firms will switch to performing. With an expected subsidy of less than 10%, 91.49% of firms will switch. For all nonperformers to switch, we need to arrive to a subsidy equal to the maximum estimated trigger subsidy, 29.84%. The mean trigger subsidy estimated is 4.57%.

Table C4. 4 Subsidy inducement effects

Subsidies Required to engage in R&D			Impact of subsidy withdrawal	Intens. marg.
(-) Profitability gaps (% obs.)[a]	Trigger subsidy values (%)	Obs. by trigger subsidy values (%)	% of (+) Profitability gaps with subsidy that become (-) without	Change in private effort (%)[c]
	≤1	31.23		-0.84[d]
55.48	$1< \rho_i \leq 10$	60.26	0.1[b]	-8.48[d]
	>10 (max. 29.84)	8.51		-17.11[d]
	4.57 (mean trigger sub.)		91.46 (mean exp. sub.)	

Notes:
a Firms with negative gaps even with currently expected subsidy.
b This 0.1% corresponds to the firms that run into negative gaps when expected subsidy is not accounted for. We have only 4 firms for which this happens.
c The change in private effort from no subsidy to subsidy is calculated as $\left[(1-\rho_{it})^{-(\beta-1)}-1\right]*100$, where β is the coefficient associated to the subsidy variable in the optimal R&D effort equation.
d The previous expression for calculation of changes in private effort as a consequence of the subsidy is evaluated at subsidy values of 1%, 10% and 20%, respectively.

The role of a subsidy withdrawal

To evaluate this effect, we have to take into account that some firms carry out R&D because the support effect of the expected subsidy fills in the negative profitability gap that would exist in its absence. Hence, we have to identify the observations for which the profitability gap evaluated under the expected subsidy share (the one in (16)) is positive, but evaluated when this subsidy is zero (as in (15)) becomes negative.

Table C4.4 also reports the effects of subsidy withdrawal on performing firms. Surprisingly, subsidy withdrawal does not affect a significant proportion of performing observations, since only 0.1% of them (of positive gap observations) will abandon R&D activities in case the subsidy disappears. Expected subsidies for the firms that would abandon R&D activities in the absence of subsidies are quite high, with a mean value of 91.46%. For the ones that would not abandon the activity even without subsidies, this mean is quite low and equal to 0.45%. All these results suggest that most of the firms being financed by subsidies for the performance of R&D and effectively performing R&D, would have performed R&D even in the absence of getting public funding. This happens because they have positive profitability gaps both under the existence of subsidies and the suppression of them. The public funding will be stimulating the performance of R&D activities for only this 0.1% observations of performing firms. Hence, public agencies are picking up for funding many firms that would have invest in R&D in any case.

4.6.2. R&D effort of R&D performers (intensive margin)

Finally, public policy is interested in knowing how subsidies change the R&D effort of firms that invest in R&D. To evaluate this question, we use the approximate measure of change in effort due to subsidies employed in González *et al.* (2005):

$$(17) \quad \frac{\left(1-\rho_{it}^{*}\right)\varepsilon\left(\rho_{it}^{*}\right)-\varepsilon\left(0\right)}{\varepsilon\left(0\right)}=\frac{\left(1-\rho_{it}^{*}\right)\varepsilon\left(\rho_{it}^{*}\right)}{\varepsilon\left(0\right)}-1=\left[\left(1-\rho_{it}^{*}\right)^{-(\beta-1)}-1\right]$$

where ε is "effort" as measured by the ratio of R&D over sales, $\varepsilon\left(\rho_{it}^{*}\right)$ is *total* effort with subsidy (*total* means joining together privately and publically funded R&D), $\varepsilon(0)$ is *total* effort with zero subsidy (here *total* means only private funding) and, finally, $\left(1-\rho_{it}^{*}\right)\varepsilon\left(\rho_{it}^{*}\right)$ corresponds to private effort when R&D is subsidized. Both $\varepsilon\left(\rho_{it}^{*}\right)$ and $\varepsilon(0)$ are determined by the optimal effort R&D equation in (7). Therefore, β is the estimated coefficient in this equation for the subsidy variable $-\ln\left(1-\rho_{it}^{*}\right)$. Depending on the value of the subsidy efficiency β, expression in (17) is equal to 0, higher than 0 or smaller than 0:

- If $\beta=1$, (17) is equal to 0. This means that private effort does not change with the subsidy as regards to the one without subsidy. The subsidy is neutral for the private effort in R&D.
- If $\beta>1$, (17) is greater than 0. This means that private effort is larger with the subsidy than it would have been without the subsidy. The subsidy increases private effort, and the *total* effort will be higher than the sum of the public share and the private effort without subsidy.
- If $\beta<1$, (17) is smaller than 0. This means that private effort is smaller with the subsidy than it would have been without the subsidy. The subsidy reduces private effort, and the *total* effort will be lower than the sum of the public share and the private effort without subsidy.

Therefore, on the one hand, we can have a crowding in effect if firms with the public support increase the private effort in R&D. On the other hand, we can have a crowding out effect if firms reduce their private effort in R&D in the presence of public support. According to our estimation results for β (equal to 0.159, see Table C4. 3), we get evidence of crowding out. This crowding out effect grows with the size of the subsidy, since for subsidies going from 1% to 10% and from here to 20%, it is respectively -0.84%, -8.48% and -17.11% (as shown in the final column of Table C4.4). These numbers indicate the percent decrease in private effort as a consequence of the subsidy.

4.7. Conclusion

Our interest in this study is identifying the effects over firms' private investment and decisions to perform R&D when there exists the possibility of getting public support thought subsidies for such activities. We are interested in a developing country like Ecuador where experience both in the provision of subsidies and private investment in R&D by firms has not a long tradition.

We use the currently available two non-overlapping waves of the National Innovation Activities Survey 2013 and 2015 (NIAS) "*Encuesta Nacional de Actividades de Innovación*", which provides firm-level data information for the periods 2009-2011 and 2012-2014, respectively, for Ecuadorian firms. Methodologically, we rely on González *et al.* (2005) and Arqué-Castells and Mohnen (2015) analytical framework to illustrate how public subsidies affect optimal R&D decisions. In their model, firms react to expected subsidies when taking optimal decisions about performance of R&D and effort in the investment. The estimation methods deal with both simultaneity issues as regards subsidies and R&D investment decisions and also selection concerns. Selectivity concerns have to do with non-random selection for firms in the group of successful applicants and likely non-random selection into the performance of R&D activities.

In what follows we summarize the main results from our study in the different steps involved in estimation. First, we predict expected subsidies for all firms in the sample by estimation of a Type-II *Tobit* model (also known as sample selection model) and find that on the one side, successful applicants seem to be firms with likely financial constraints to invest in R&D projects. Also, there seems to be a preference from public agencies to finance firms with certain technological sophistication (as measured by the existence of one department for ICT) and higher risk from export markets. On the other hand, some other results indicate that public agencies are not probably only picking firms with potential but facing market failures, but also cherry picking quite established firms in terms of sales, market power and good business expectations. Second, we estimate another Type-II *Tobit* model for the firm's yes/no R&D decision and the optimal firm's R&D investment effort. Both equations include among regressors a variable depending on the firm's expected subsidy. Results from these equations show that the higher the expected subsidy the more likely the firm performs R&D and the higher the investment optimal effort. Hence, firms' public subsidies to R&D in Ecuador increase the *total* firm's effort in R&D investment. However, the estimated value for the subsidy variable in the R&D optimal effort equation indicates the presence of a partial *crowding out* effect of public funding as regards private investment. This means that private effort is smaller with the subsidy than it would have been without the subsidy.

Third, from the inducement (or extensive margin) effects of the subsidy we reach two conclusions: 1) with an expected subsidy of about 10%, about 91% of non-R&D performing firms will move into performers; and, 2) subsidy withdrawal only affects a very little percentage of firms that would abandon performance of R&D (0.1%). The latter indicates that public funding is being directed to a high extent to firms that would have performed R&D even in the absence of public funding.

Since Ecuador has not a strong tradition in firms' innovation activities, it is generally good that public funding increases the *total* firm's R&D effort. But probably both the country public agency and the firms in the country need a longer period to exploit the process of "learning by doing" associated to the provision of public support. The *crowding out* effect found in the data could be signalling that may be public agencies should be clearer in their requirements for the use of these resources, otherwise some firms might have incentives to deviate the money for other firms' investments, mainly firms that suffer from some financial constraints. There can also indicate a mismatch between firms' expected profits from innovative activities and what they really get from innovation. If expectations are better than reality, they can adapt their R&D expenditure by not risking so much their own money and substituting it partially by the public funds.

As for other variables included to explain both the performance of R&D and its intensity, we found the following. First, better demand prospects and higher sensibility of consumers to firms' innovation, encourage performance and higher effort in the investment. Second, the more the technological opportunities available to firms, the higher the effort. Finally, more firms' market power discourages R&D effort and more competition creates incentives to R&D ("scape competition effect", Arrow, 1962). This indicates that Ecuador can also encourage autonomous firms' incentives to invest in R&D and to intensify effort by promoting in the country better demand conditions, wider access to information and knowledge about technological opportunities, and more competitive product markets.

Appendix C4. 1 R&D effort and sourcing of investments in Ecuador

Year	Country R&D as % of GDP	% of intramural R&D performed by Business Enterprises (independent of source)	% of intramural R&D in the country financed by different sources: Business Enterprises	% of intramural R&D in the country financed by different sources: Government
1996	0.074	4.04	n/a	79.73
1997	0.062	4.38	n/a	80.11
1998	0.065	4.75	n/a	90.61
1999	n/a	n/a	n/a	n/a
2000	n/a	n/a	n/a	n/a
2001	0.051	13.49	n/a	n/a
2002	0.055	11.39	n/a	n/a
2003	0.057	12.90	n/a	n/a
2004	n/a	n/a	n/a	n/a
2005	n/a	n/a	n/a	n/a
2006	0.128	17.44	17.44	69.27
2007	0.131	21.55	21.55	58.10
2008	0.227	8.53	8.53	89.56
2009	0.394	40.85	0.19	41.21
2010	0.402	43.40	1.00	40.18
2011	0.339	58.12	0.42	28.45
2012	0.332	57.25	0.06	28.76
2013	0.379	49.06	0.03	35.79
2014	0.441	42.30	0.12	42.40

Source: UNESCO Institute for Statistics, 2017.

Appendix C4. 2 Public Investment in R&D

Year	**Public R&D (in USD Dollars)[a]**
2011	2.194.543
2012	9.217.283
2013	25.252.838
2014	38.962.570
2015	12.272.869

a: Amount for the projects named “R&D” in the National Budget Execution.
Source: Ministry of Finance (Government of Ecuador)

Appendix C4. 3 Variables Description

Variables	Description
bsidy share	Fraction of R&D and related innovation expenditures funded by the public sector. This variable is in log form.
*d*_Subsidy	Dummy variable taking value 1 if the firm receives a subsidy for funding R&D and related innovation expenditures, and 0 otherwise.
R&D Effort	Total expenditure in R&D and other related innovation expenditures over firms' sales. The amount of expenditure includes intramural R&D, extramural R&D and other innovation expenditure. Both numerator and denominator aggregate in real terms the corresponding values of these variables for the three-year period of each wave of the survey. We use the Ecuador Supply Price Index. This variable is in log form.
*d*_R&D	Dummy variable taking value 1 if the firm invests in R&D or related innovation activities, and 0 otherwise.
Expected Subsidy share	Expected fraction of R&D and related innovation expenditures to be funded by the public sector. It is obtained as a prediction from the Tobit-type II model for the subsidy share equation.
Size *t-2*	Number of employees of the firm. This variable is in log form.
*d*_ICT	Dummy variable taking value1 if the firm has a formal department of Information and Communication Technologies (ICT).
Export Intensity *t-2*	Total exports over firm's sales in the period *t-2*. This variable is in log form.
*d*_export *t-2*	Dummy variable taking value 1 if the firm exports in period *t-2*, and 0 otherwise.
*d*_foreign	Dummy variable taking value 1 if the firm has foreign capital in more than 50%, and 0 otherwise.
*d*_group	Dummy variable taking value 1 if the firm is member of a business group, and 0 otherwise.
Age	Number of years since the firm was born. This variable is in log form.
Market share *t-2*	Firms' sales over industry sales in period *t-2*. The industry sales are at 2 digit level from ISIC Rev.4 classification.
*d*_fixed investment *t-2*	Dummy variable taking value 1 if the firm invests in fixed capital in period *t-2*, and 0 otherwise.
Marketing intensity *t-2*	Marketing innovative expenditures over sales. This variable includes the advertising expenditure. This variable is in log form.
Prices by demand and discounts	Dummy variable taking value 1 if the firm has introduced for the first time new methods for setting prices such as varying prices depending on the level of demand or discount systems to customers, and 0 otherwise.
Unsatisfied demand	The ratio of innovative firms in your sector-wave of the survey (at 3-digit sector level according to ISIC Rev 4. classification) that declare as reason for performing activities directed to innovation, the detection of an unsatisfied demand in the product market.
Scientific-technical opportunities	The ratio of innovative firms in your sector-wave of the survey (at 3-digit sector level according to ISIC Rev 4. classification) that declare as reason for performing activities directed to innovation, the possibility of exploiting ideas or scientific and technical novelties.
Lack of technological information	The higher the value of this indicator, the higher the relative importance for a sector in a particular wave of the survey (at 3-digit sector level according to ISIC Rev 4. classification) of the obstacle for innovation of lack of knowledge and information about technology.
Environmental concern	The higher the value of this indicator, the higher the relative importance for a sector in a particular wave of the survey (at 3-digit sector level according to ISIC Rev 4. classification) of the objective of reducing environmental damages when pursuing innovation.
Quality improvement	The higher the value of this indicator, the higher the relative importance for a sector in a particular wave of the survey (at 3-digit sector level according to ISIC Rev 4. classification) of the objective of improving the quality of products when pursuing innovation.
*d*_skill	Dummy variable taking value 1 if the firm has employees with PhDs, Master or some University degree, and 0 otherwise.
*d*_protection	Dummy variable taking value 1 if the firm uses at least one appropriability instrument or protection mechanism (brand names, patents, utility models, industrial design, author's copyrights, designations of origin, confidentiality clauses for workers, or confidentiality contracts with suppliers and customers), and 0 otherwise.
Relative productiv. *t-2*	The denominator of this ratio is the sector mean of the sales per employee (in log terms) at 3-digit sector level according to ISIC Rev 4. classification. The numerator is the sales per employee (in log terms) of the firm. Both parts use the period *t-2*.
Relative productiv. ^{2} *t-2*	Square of the relative productivity in period *t-2*
Low tech manufacturing	Dummy variable taking value 1 if the firm is in manufacturing low technology intensity sectors according to NACE Rev. 2 classification, and 0 otherwise.
Med-Low tech manufacturing	Dummy variable taking value 1 if the firm is in manufacturing Medium Low technology intensity sectors according to NACE Rev. 2 classification, and 0 otherwise.
Med-High tech manufacturing	Dummy variable taking value 1 if the firm is in manufacturing Medium High technology intensity sectors according to NACE Rev. 2 classification, and 0 otherwise.
High tech manufacturing	Dummy variable taking value 1 if the firm is in manufacturing High technology intensity sectors according to NACE Rev. 2 classification, and 0 otherwise.
Non-knowledge intensive services	Dummy variable taking value 1 if the firm is in Service Less Knowledge intensive sectors according to NACE Rev. 2 classification, and 0 otherwise.
Knowledge intensive services	Dummy variable taking value 1 if the firm is in Service Knowledge intensive sectors according to NACE Rev. 2 classification, and 0 otherwise.
Other sectors	Dummy variable taking value 1 if the firm is in not Manufacturing or services sectors according to ISIC Rev 4 classification, and 0 otherwise.

Variables	Description
*d*_geographical	Dummy variable taking value 1 if the firm is from Guayas, Pichincha or Azuay provinces, and 0 otherwise.
*d*_time	Dummy variable taking value 1 for observations corresponding to the second wave of the survey, and 0 otherwise.

Appendix C4. 4 Descriptive statistics

Variables	mean (sd.)
Subsidy share (%)	0.69
	(6.46)
*d*_Subsidy	0.02
	(0.14)
R&D Effort (%)	2.98
	(38.77)
*d*_R&D	0.44
	(0.50)
Expected Subsidy share (%)	0.27
	(3.99)
Size *t-2* (log number employees)	3.44
	(1.42)
*d*_ICT	0.31
	(0.46)
Export Intensity *t-2* (%)	4.59
	(18.51)
*d*_export *t-2*	0.12
	(0.32)
*d*_foreign	0.10
	(0.31)
*d*_group	0.17
	(0.38)
Age (log)	2.65
	(0.81)
Market share *t-2* (%)	1.45
	(5.82)
*d*_fixed investment *t-2*	0.45
	(0.50)
(novel) Marketing intensity *t-2* (%)	0.26
	(2.21)
Prices by demand and discounts	0.05
	(0.22)
Unsatisfied demand	0.49
	(0.18)
Scientific-technical opportunities	0.97
	(0.14)
Lack of technological information	0.35
	(0.17)
Environmental concern	0.89
	(0.17)
Quality improvement	1.26
	(0.17)
*d*_skill	0.90
	(0.30)

Variables	mean (sd.)
*d*_protection	0.30
	(0.46)
Relative productivity *t-2*	1.00
	(0.23)
Relative productivity^2 *t-2*	1.05
	(0.35)
Low tech manufacturing	0.17
	(0.37)
Med-Low tech manufacturing	0.09
	(0.29)
Med-High tech manufacturing	0.04
	(0.19)
High tech manufacturing	0.01
	(0.09)
Non-knowledge intensive services	0.19
	(0.39)
Knowledge intensive services	0.37
	(0.48)
Others sectors	0.13
	(0.33)
*d*_geographical	0.64
	(0.48)
*d*_time	0.69
	(0.46)
Observations	9,090

Chapter 5: Conclusion

In this final Chapter we include the general results that we have obtained in the three main Chapters in this Thesis (Chapters 2, 3 and 4). As we have acknowledged since the beginning of this Thesis work, the Ecuadorian economy is still heavily dependent on oil prices and agriculture. In such an environment, that is many times affected by high volatility and uncertainty, the Ecuadorian government is interested in transforming the economy into a more knowledge based one. However, little is known for this country about the effects of innovation activities on firms' performance in order to properly improve public policies. Specifically, the focus of this Thesis has been to fill in the gap on questions such as which are the effects of different types of innovation activities on firms' performance measures that are relevant for countries and, even more, for a developing country like Ecuador that still lacks behind the achievements of other countries in terms of technological leadership. The different performance measures included in this Thesis are productivity, markups and employment growth. In addition, the Thesis has also considered which has been the role of public subsidies in encouraging firms' investments and efforts in innovative expenditures, to be able to assess the effectiveness of this type of instrument to promote firms' private investment in these activities.

In what follows, we summarize the main results we have obtained in the core three Chapters in this Thesis.

Summary of results from Chapter 2: *"ICT use, investments in R&D and workers training, firms' productivity and markups: The case of Ecuadorian manufacturing"*

As regards the questions raised up in this Chapter, we can summarise results as follows. First, the variables included to signal professionalization and good business practices in Ecuadorian manufacturing firms, such as belonging to an enterprise network, having access to finance, performing activities of market research, accountancy, and having environmental concerns, explain both higher propensities to invest in R&D, workers training, and ICT use, and also higher R&D and workers training intensities (for ICT use the database does not contain information about amounts of investment).

Second, the three considered innovation activities have a positive and relevant effect on firms' TFP, with an estimated elasticity for R&D intensity around 0.05, for workers training intensity 0.06, and a semi-elasticity for ICT use that implies that performing this activity justifies around 34% higher TFP. Third, they are also relevant to explain higher firms' markups, since the statistically significant estimated elasticity for R&D intensity in the markups regression is around 0.11, for workers training intensity 0.01, and the semi-elasticity for ICT use justifies around 42% higher markups.

Additionally, the estimated markups regression that includes among regressors the variable TFP allows discerning whether innovation activities influence markups by affecting efficiency and/or by affecting firms' capacity to set prices. In particular, we obtain that around half of the effect of R&D intensity on markups acts through increasing firms' efficiency, and the other half through higher selling prices. For ICT, around three quarters are explained by higher efficiency and one quarter by higher prices. Innovation activities probably generate higher quality products. Interpretation of results for workers training investments is more complex, since it likely points out to a situation where there is more than full pass-through from marginal costs reductions to reductions in prices.

Worth mentioning are results for the variables market research and main customer being foreigner. The realization of market research activities by the firm is associated both to higher propensity to perform R&D and workers training investments and to higher intensity in these investments. This may point out some demand problems requiring innovations. This is reinforced by the fact that market research is associated to lower markups in the markups regressions (demand conditions pressuring prices to go down). The positive association between main customer being foreigner and R&D and workers training intensities may suggest that learning and competition from international markets encourages firms' innovation efforts. Its effect on markups is also positive, this time probably indicating that firms which main customer is foreigner are able to charge higher prices (likely related to better quality products).

As regards firms' geographical location, Pichincha is in general outperforming other Ecuadorian provinces in terms of R&D, workers training, ICT use, TFP, and markups. Furthermore, private company is the legal form associated with higher TFP and with higher markups (also local government companies are associated with higher markups). Among industries, Chemicals is the industry that stands out in all analysed dimensions.

Summary of results from Chapter 3: *"Innovation and employment growth in Ecuadorian firms"*

Our results indicate that different types of innovations may have different effects on employment. Process innovation by increasing production efficiency over time decreases firms' demand for labour (*displacement effect*). Firms in homogeneous industries might be interested in becoming more competitive to survive in such environments by the introduction of process innovations. However, organizational innovation does not display a statistically significant effect on employment. Differently, growth in sales due to new products generates a *gross* increase in firms' labour demand since efficiency in the production of old products is higher than in the production of new ones (the opposite of a *displacement effect*) and since firms need to increase the number of employees to cover this new "demand". In addition, the *net* effect of product innovation on employment growth, which takes into account a certain degree of cannibalization of old products by new ones in product innovative firms, is still positive, large and highly significant, although smaller than the *gross* effect. This evidences that product innovators suffer from a decrease in demand of old products (in line with Schumpeter's, 1942, theory about creative destruction). However, we do not find evidence in favour of a business stealing effect from product innovators on sales growth for non-product innovators. Finally, we find evidence about marketing innovation also increasing employment growth by very likely increasing firms' profits through the increase in prices of new products as regards old ones. The effect of marketing innovation on employment growth represents a novelty explored in this Chapter, since previously related papers do not consider this type of innovation and its separated effect on employment.

Overall, the positive effects of innovation on employment (from product and marketing innovations) exceed the negative ones (from process innovation, and from some cannibalization of old products by new ones inside product innovative firms).

In a second set of supplementary results in the Chapter, where we try to find some evidence about the quality of generated jobs, we find that innovative firms require higher proportions of skilled labour (driven by the success of product innovations as measured by sales growth due to new products) and pay higher average wages *per* employee. Process innovation seems to have a skill-bias effect in favour of unskilled labour. Hence, it seems that process innovations in Ecuador are targeting improvements in efficiency of more repetitive, automatic and simple tasks, which are not so demanding of skills. This makes compatible process innovation not only displacing labour but making it in a bias way against labour force with higher skills. Differently, product innovation in Ecuador seems to be related to more complex innovations that probably in the short and medium run are produced less efficiently than old products but require more skilled labour. This works in favour of product innovation both affecting positively employment growth and making this growth bias towards more skill workers.

To sum up, innovation not only has *net* employment effects in the economy, but we also find some evidence in favour of innovative activities by firms also positively influencing the quality of generated jobs in terms of skills and wages.

Summary of results from Chapter 4: *“Public support effectiveness on innovation effort in Ecuadorian firms”*

In what follows we summarize the main results from our study in this Chapter and corresponding to the different steps involved in estimation. First, we predict expected subsidies for all firms in the sample by estimation of a Type-II *Tobit* model (also known as sample selection model) and find that, on the one side, successful applicants seem to be firms with likely financial constraints to invest in R&D projects. Also, there seems to be a preference from public agencies to finance firms with certain technological sophistication (as measured by the existence of one department for ICT) and higher risk from export markets. On the other hand, some other results indicate that public agencies are not probably only picking firms with potential but facing market failures, but also cherry picking quite established firms in terms of sales, market power and good business expectations. Second, we estimate another Type-II *Tobit* model for the firm's yes/no R&D decision and the optimal firm's R&D investment effort. Both equations include among regressors a variable depending on the firm's expected subsidy. Results from these equations show that the higher the expected subsidy the more likely the firm performs R&D and the higher the optimal investment effort. Hence, firms' public subsidies to R&D in Ecuador increase the *total* firm's effort in R&D investment. However, the estimated value for the subsidy variable in the R&D optimal effort equation indicates the presence of a partial *crowding out* effect of public funding as regards private investment. This means that private effort is smaller with the subsidy than it would have been without the subsidy.

Third, from the inducement (or extensive margin) effects of the subsidy we reach two conclusions: 1) with an expected subsidy of about 10%, about 91% of non-R&D performing firms will move into performers; and, 2) subsidy withdrawal only affects a very little percentage of firms that would abandon performance of R&D (0.1%). The latter indicates that public funding is being directed to a high extent to firms that would have performed R&D even in the absence of public funding.

As for other variables included to explain both the performance of R&D and its intensity, we found the following. First, better demand prospects and higher sensibility of consumers to firms' innovation, encourage performance and higher effort in the investment. Second, the more the technological opportunities available to firms, the higher the effort. Finally, more firms' market power discourages R&D effort and more competition creates incentives to R&D ("scape competition effect", Arrow, 1962). This indicates that Ecuador can also encourage autonomous firms' incentives to invest in

R&D and to intensify effort by promoting in the country better demand conditions, wider access to information and knowledge about technological opportunities, and more competitive product markets.

References

Aboal, D., Garda, P., 2015. Does public financial support stimulate innovation and productivity? An impact evaluation. CEPAL Review .

Aboal, D., Tacsir, E., 2015. Innovation and Productivity in Services and Manufacturing: The Role of ICT Investment. IDB Working Paper Series IDB-WP-658.

Aboal, D., Garda, P., Lanzilotta, B., Perera, M., 2015. Does Innovation Destroy Employment in the Services Sector? Evidence from a Developing Country. Emerging Markets Finance and Trade 51, 558-577.

Acemoglu, D., 1998. Why Do New Technologies Complement Skills? Directed Technical Change and Wage Inequality. The Quarterly Journal of Economics 113, 1055-1089.

Acs, Z.J., Audretsch, D.B., 1988. Innovation in large and small firms: an empirical analysis. American Economic Review , 678-690.

Aghion, P., Howitt, P., 1998. Endogenous Growth Theory. The MIT Press .

Aghion, P., Howitt, P., 1992. A model of growth through creative destruction. Econometrica 60, 323-351.

Aghion, P., Bloom, N., Blundell, R., Griffith, R., Howitt, P., 2005. Competition and Innovation: an Inverted-U Relationship. The Quarterly Journal of Economics 120, 701-728.

References

Almus, M., Czarnitzki, D., 2003. The Effects of Public R&D Subsidies on Firms' Innovation Activities: The Case of Eastern Germany. Journal of Business & Economic Statistics 21, 226-236.

Álvarez, R., Benavente, J.M., Camposano, R., Cuevas, C., 2011. Employment generation, firm size, and innovation in Chile. IDB-TN 319.

Añón, D., Manjón, M., Mañez, J., 2011. Multinationals, R&D, and productivity: evidence for UK manufacturing firms. Industrial and Corporate Change 20, 641-659.

Añón-Higón, D., 2012. The impact of ICT on innovation activities: Evidence for UK SMEs. International Small Business Journal 30, 684-699.

Arqué-Castells, P., Mohnen, P., 2015. Sunk Costs, Extensive R&D Subsidies and Permanent Inducement Effects. The Journal of Industrial Economics 63, 458-494.

Arrow, K.J., 1962. Economic welfare and the allocation of resources for inventions, in Nelson, R,R, (Ed.), The Rate and Direction of Inventive Activity. Princeton University Press, Princeton, pp. 609-625.

Audretsch, D.B., Klomp, L., Santarelli, E., Thurik, A.R., 2004. Gibrat's Law: Are the Services Different? Review of Industrial Organization 24, 301-324.

Autor, D.H., Dorn, D., 2013. The Growth of Low-Skill Service Jobs and the Polarization of the US Labor Market. American Economic Review 103, 1553-1597.

Aw, B.Y., Roberts, M., J., Xu, D.Y., 2011. R&D Investment, exporting and productivity dynamic. American Economic Review 101, 1312-1344.

Aw, B.Y., Roberts, M., J., Xu, D.Y., 2007. Export market participation, investments in R&D and worker training, and the evolution of firm productivity. World Economy 30, 83-104.

Banco Central del Ecuador, 2014. Información Estadística Mensual No.1947. 2017.

Barras, R., 1986. Towards a theory of innovation in services. Research Policy 15, 161-173.

Benavente, J.M., 2006. The role of research and innovation in promoting productivity in Chile. Economics of Innovation and New Technology 55, 301-315.

Benavente, J.M., Lauterbach, R., 2008. Technological innovation and employment: complements or substitutes? The European Journal of Development Research 20, 318-329.

Black, S.E., Lynch, L.M., 2001. How to compete: the impact of workplace practices and information technology on productivity. Review of Economics and statistics 83, 434-445.

Bloom, N., Darca, M., Kretschmer, T., Sadun, R., Van Reenen, J., 2010. The economic impact of ICT. Centre for Economic Performance, LSE .

Bloom, N., Griffith, R., Van Reenen, J., 2002. Do R&D tax credits work? Evidence from a panel of countries 1979–1997. Journal of Public Economics 85, 1-31.

Bogliacino, F., Lucchese, M., 2016. Endogenous skill biased technical change: testing for demand pull effect. Industrial and Corporate Change 25, 227-243.

References

Bontempi, M.E., Mairesse, J., 2015. Intangible capital and productivity at the firm level: a panel data assessment. Economics of Innovation and New Technology 24, 22-51.

Bratti, M., Felice, G., 2012. Are exporters more likely to introduce product innovation? The World Economy 35, 1559-1598.

Bresnahan, T.F., Trajtenberg, M., 1995. General purpose technologies 'Engines of growth'? Journal of Econometrics 65, 83-108.

Bresnahan, T.F., Brynjolfsson, E., Hitt, L.M., 2002. Information Technology, Workplace Organization, and the Demand for Skilled Labor: Firm-Level Evidence. The Quarterly Journal of Economics 117, 339-376.

Busom, I., Corchuelo, B., Martínez-Ros, E., 2017. Participation inertia in R&D tax incentive and subsidy programs. Small Business Economics 48, 153-177.

Busom, I., Corchuelo, B., Martínez-Ros, E., 2014. Tax incentives... or subsidies for business R&D? Small Business Economics 43, 571-596.

Busom, I., Vélez-Ospina, J.A., 2017. Innovation, Public Support, and Productivity in Colombia. A Cross-industry Comparison. World Development 99, 75-94.

Caroli, E., Van Reenen, J., 2001. Skill-Biased Organizational Change? Evidence from A Panel of British and French Establishments. The Quarterly Journal of Economics 116(4), 1149-1192.

Cassiman, B., Golovko, E., Martínez-Ros, E., 2010. Innovation, exports and productivity. International Journal of Industrial Organization 28, 372-376.

Cirera, X., Sabetti, L., 2016. The Effects of Innovation on Employment in Developing Countries: Evidence from Entreprise Survey. Policy Research Working Papers 775.

Colombo, E., Stanca, L., 2014. The impact of training on productivity: evidence from a panel of Italian firms. International Journal of Manpower 35, 1140-1158.

Commander, S., Harrison, R., Menezes-Filho, N., 2011. ICT and productivity in developing countries: new firm-level evidence from Brazil and India. Review of Economics and Statistics 93, 528-541.

Congreso Nacional del Ecuador, 1998. Ley de Defensa del Artesano. http://www.artesanos.gob.ec/wpcontent/uploads/downloads/2014/05/ley_defensa_artesano. pdf .

Corrado, C., Hulten, C., Sichel, D., 2009. Intangible Capital and U.S. economic growth. Rev. Income Wealth 55, 661-685.

Crass, D., Peters, B., 2014. Intangible assets and firm-level productivity. Discussion Paper 14-120.

Crépon, B., Duguet, E., Mairesse, J., 1998. Research and Development, Innovation and Productivity: An Econometric Analysis at the Firm Level . Economics of Innovation and New Technology 7 (2), 115-158.

References

Crespi, G., Tacsir, E., 2012. Effects of Innovation on Employment in Latin American. IDB-TN 496.

Crespi, G., Zúñiga, P., 2012. Innovation and productivity: evidence from six Latin American countries.   . World Development 40 (2), 273–290.

Czarnitzki, D., Lopes Bento, C., 2012. Evaluation of Public R&D Policies: A Cross-Country Comparison. World Review of Science, Technology and Sustainable Development 9, 254-282.

Czarnitzki, D., Lopes-Bento, C., 2013. Value for money? New microeconometric evidence on public R&D grants in Flanders. Research Policy 42, 76-89.

Dachs, B., Hud, M., Koehler, C., Peters, B., 2017. Employment Effects of innovation over the Business Cycle: firm-level evidence from European countries. SWPS-2017 03.

Dachs, B., Peters, B., 2014. Innovation, employment growth, and foreign ownership of firms: A European perspective. Research Policy 43, 214-232.

Daimer, S., Diekmann, J., Jung-Erceg, P., Schricke, E., Schubert, T., Som, O., Stehnken, T., Solberg, E., 2012. Organizational and marketing innovation - promises and pitfalls? PRO INNO Europe: INNO-Grips II report .

Damijan, J.P., Kostevc, Č., Stare, M., 2014. Impact of innovation on employment and skill upgrading. Simpatic working paper 7.

David, P.A., Hall, B., Toole, A.A., 2000. Is public R&D a complement or substitute for private R&D? A review of the econometric evidence. Research Policy 29, 497-529.

de Elejalde, R., Giuliodori, D., Stucchi, R., 2015. Employment and Innovation: Firm-Level Evidence from Argentina. Emerging Markets Finance and Trade 51, 27-47.

de Elejalde, R., Giuliodori, D., Stucchi, R., 2011. Employment Generation, Firms Size and Innovation: Microeconometric Evidence from Argentina. IDB-TN 313.

De Loecker, J., Warzynski, F., 2012. Markups and firm-level export status. American Economic Review 102, 2437-2471.

Doraszelski, U., Jaumandreu, J., 2013. R&D and Productivity: Estimating endogenous productivity. Review of Economic Studies 80, 1338-1383.

Edquist, H.O., Henrekson, M., 2016. Do R&D and ICT Affect Total Factor Productivity Growth Differently? IFN Working Paper 1108.

Evangelista, R., Vezzani, A., 2012. The impact of technological and organizational innovations on employment in European firms. Industrial and Corporate Change 21, 871-899.

Falk, M., 2015. Employment effects of technological and organizational innovations: Evidence based on linked Firm-Level Data for Austria, Journal of Economics and Statistics 253(3), 268-285.

References

Fernández-Sastre, J., Martín-Mayoral, F., 2015. The effects of developing-countries' innovation support programs: evidence from Ecuador. Innovation: Organization & Management 17, 466-484.

Flikkema, M., Jansen, P., Van, D.S., 2007. Identifying Neo-Schumpeterian Innovation in Service Firms: A Conceptual Essay with a Novel Classification. Economics of Innovation and New Technology 16, 541-558.

García, A., Jaumandreu, J., Rodríguez, C., 2004. Innovation and jobs: evidence from manufacturing firms MPRA Paper 1204.

Gibrat, R., 1931. Les Inégalités Économiques: Applications: Aux Inégalités Des Richesses, à La Concentration Des Entreprises, Aux Populations Des Villes, Aux Statistiques Des Familles, etc., d'Une Loi Nouvelle, La Loi De l'Effect Proportionnel. Recueil Sirey, Paris.

Giuri, P., Torrisi, S., Zinovyeva, N., 2008. ICT, skills, and organizational change: evidence from Italian manufacturing firms. Industrial and Corporate Change 17, 29-64.

González, X., Jaumandreu, J., Pazó, C., 2005. Barriers to Innovation and Subsidy Effectiveness. The Rand Journal of Economics 36, 930-950.

Gourieroux, C., Monfort, A., 1996. Simulation-Based Econometric Methods. Oxford university press.

Greenan, N., 2003. Organisational change, technology, employment and skills: an empirical study of French manufacturing. Cambridge Journal of Economics 27, 287-316.

Greenan, N., Mairesse, J., Topiol-Bensaid, A., 2001. Information technology and research and development impacts on productivity and skills: Looking for correlations on French firm level data. NBER Working Paper Series 8075.

Greene, W., H., 2003. Econometric Analysis, 5th Edition ed. Prentice Hall, New York.

Griliches, Z., 1979. Issues in assessing the contribution of R&D to productivity growth. Bell Journal of Economics 10, 92-116.

Griliches, Z., 1970. R&D and the productivity slowdown. American Economic Review 2, 343-348.

Hajivassiliou, V., A., Ruud, P., A., 1994. Chapter 40 Classical estimation methods for LDV models using simulation, in Engle, R., McFadden, D. (Eds.), Handbook of Econometrics, Amsterdam: North-Holland, pp. 2383-2441.

Hall, B., 2011. Innovation and productivity. UNIT-MERIT Working Paper Series 2011-028 .

Hall, B., Lerner, J., 2010. The financing of R&D and Innovation, in Hall, B., Rosenberg, N. (Eds.), Handbook of the Economics of Innovation. Elsevier-North, Amsterdam, The Netherlands.

Hall, B., Lotti, F., Mairesse, J., 2013. Evidence on the impact of R&D and ICT investments on innovation and productivity in Italian firms. Economics of Innovation and New Technology 22, 300-328.

References

Hall, B., Lotti, F., Mairesse, J., 2009. Innovation and productivity in SMEs: empirical evidence for Italy. Small Business Economics 33, 13-33.

Hall, B., Lotti, F., Mairesse, J., 2008. Employment, innovation, and productivity: evidence from Italian microdata. Industrial and Corporate Change 17, 813-839.

Hall, B., Maffioli, A., 2008. Evaluating the impact of technology development funds in emerging economies: evidence from Latin America. The European Journal of Development Research 20, 172-198.

Hall, B., Van Reenen, J., 2000. How Effective are Fiscal Incentives for R&D? A Review of the Evidence. Research Policy 29, 449-469.

Harrison, R., Jaumandreu, J., Mairesse, J., Peters, B., 2008. Does innovation stimulate employment? A firm-level analysis using comparable micro-data from four European countries. National Bureau of Economic Research Working Paper 14216.

Harrison, R., Jaumandreu, J., Mairesse, J., Peters, B., 2014. Does innovation stimulate employment? A firm-level analysis using comparable micro-data from four European countries. International Journal of Industrial Organization 35, 29-43.

Heckman, J., 1979. Sample Selection Bias as a Specification Error. Econometrica 47, 153-161.

Huergo, E., Moreno, L., 2017. Subsidies or loans? Evaluating the impact of R&D support programmes. Research Policy 46, 1198-1214.

Huergo, E., Trenado, M., Ubierna, A., 2016. The impact of public support on firm propensity to engage in R&D: Spanish experience. Technological Forecasting and Social Change 113, 206-219.

INEC, 2010. Economic Census of Ecuador.

International Labour Office, 2009. Guide to the New Millennium Development Goals Employment Indicators Including the Full Set of Decent Work Indicators . International Labour Office, Geneva.

ITU, 2012. Overview of the internet of things. Recommendation ITU-T Y.2060. Geneva: International Telecommunication Union .

Jaumandreu, J., 2003. Does innovation spur employment? A firm-level analysis using Spanish CIS data. Mimeo .

Junge, M., Severgnini, B., Sørensen, A., 2015. Product-Marketing Innovation, Skills, and Firm Productivity Growth. Review of Income and Wealth 62 (4), 724-757.

Konings, J., Vanormelingen, S., 2015. The impact of training on productivity and wages: firm-level evidence. Review of Economics and Statistics 97, 485-497.

Lederman, D., Maloney, W.F., 2003. Research and development (R&D) and development. Policy Research Working Papers 3024.

Lederman, D., Messina, J., Pienknagura, S., Rigolini, J., 2013. Latin American Entrepreneurs: Many Firms but Little Innovation. World Bank Publications.

Levinsohn, J., Petrin, A., 2003. Estimating production functions using inputs to control for unobservables. Review of Economic Studies 70, 317–342.

Lokshin, B., Mohnen, P., 2012. How effective are level-based R&D tax credits? Evidence from the Netherlands. Applied Economics 44, 1527-1538.

Máñez, J., A., Rochina-Barrachina, M., E, Sanchis-Llopis, J., A., 2015. The Dynamic linkages among exports, R&D and Productivity. World Economy 38, 583-612.

Marino, M., Lhuillery, S., Parrotta, P., Sala, D., 2016. Additionality or crowding-out? An overall evaluation of public R&D subsidy on private R&D expenditure. Research Policy 45, 1715-1730.

Marouani, M.A., Nilsson, B., 2016. The labor market effects of skill-biased technological change in Malaysia. Economic Modelling 57, 55-75.

Monge-González, R., Rodríguez-Alvarez, J., Hewitt, J., Orozo, J., Ruiz, K., 2011. Innovation and Employment growth in Costa Rica a Firm-level Analysis. IDB-TN 318.

Mothe, C., Nguyen-Thi, T., Uyen, 2012. Non-technolocial and technological innovation: do services differ from manufacturing? An emperical analysis of Luxembourg firms. International Journal of Technology Management 57, 227-244.

Motohashi, K., 2008. IT, enterprise reform, and productivity in Chinese manufacturing firms. Journal of Asian Economics 19, 325-333.

Murphy, M., 2002. Organisational Change and Firm Performance. OECD Science, Technology and Industry Working Papers .

Nelson, R., 1959. The simple economic of basic Scientific Research. Journal of Political Economy 49, 297-306.

OECD, 2009. Innovation in Firms. Organisation for Economic Co-operation and Development.

OECD, 2007. OECD Science, Technology and Industry Scoreboard 2007. Organisation for Economic Co-operation and Development.

OECD, 2006. Innovation and Knowledge-Intensive Service Activities. Organisation for Economic Co-operation and Development.

OECD, 2002. Frascati Manual: Proposed Standard Practice for Surveys on Research and Experimental Development.

OECD, 1997. Oslo Manual: Guidelines for Collecting and Interpreting Technological Innovation Data. Organisation for Economic Co-operation and Development Publishing, Paris.

OECD, Eurostat, 2005. Oslo Manual: Guidelines for Collecting and Interpreting Innovation Data. Organisation for Economic Co-operation and Development Publishing, Paris.

Olley, G.S., Pakes, A., 1996. The dynamics of productivity in the telecommunications equipment industry. . Econometrica 64, 1263–1297.

Peters, B., 2008. Innovation and firm performance: an empirical investigation for German firms. ZEW Economic Studies 38.

Peters, B., Riley, R., Siedschlag, I., 2013. The Influence of Technological and Non-Technological Innovation on Employment Growth in European Service Firms. Servicegap Discussion Paper 40.

Pianta, M., 2005. Innovation and Employment, in Fagerberg, J., Mowery, D, C, (Eds.), The Oxford Handbook of Innovation. Oxford Handbooks Online, pp. 568-598.

Piva, M., Santarelli, E., Vivarelli, M., 2005. The skill bias effect of technological and organisational change: Evidence and policy implications. Research Policy 34, 141-157.

Piva, M., Vivarelli, M., 2002. The Skill Bias: Comparative evidence and an econometric test. International Review of Applied Economics 16, 347-357.

Polder, M., Van Leeuwen, G., Mohnen, P., Raymond, W., 2010. Product, process and organizational innovation: drivers, complementarity and productivity effects. UNU-MERIT Working Papers Series 035.

Presidencia de la República del Ecuador, 2011. Reglamentos al Código de la Producción.

Registro Oficial, 2010. Código Orgánico de la Producción Comercio e Inversiones. 351.

Rincón, A., Vecchi, M., Venturini, F., 2013. ICT as a general purpose technology: spillovers, absorptive capacity and productivity performance. Discussion Paper 416.

Rodríguez-Moreno, J., Rochina-Barrachina, M., E, 2015. Innovación y productividad en las empresas manufactureras ecuatorianas. Cuadernos económicos de ICE , 107-136.

Roodman, D., 2011. Fitting fully observed recursive mixed-process models with cmp. Stata Journal 11, 159-206.

Rust, R., Ambler, T., Carpenter, G., Kumar, V., Srivastava, R., 2004. Measuring Marketing Productivity: Current Knowledge and Future directions. Journal of Marketing 68, 76-89.

Schubert, T., 2010. Marketing and Organisational Innovations in Entrepreneurial Innovation Processes and their Relation to Market Structure and Firm Characteristics. Review of Industrial Organization 36, 189-212.

Schumpeter, J., 1942. Capitalism, Socialism, and Democracy. New York: Harper & Bros.

Schwartz, L., Guaipatín, C., 2014. Ecuador: Análisis del Sistema Nacional de Innovación: Hacia la consolidación de una cultura innovadora. IDB-MG-223.

SENPLADES, 2013. Objetivo 10: Impulsar la transformación de la matriz productiva, in Anonymous Plan Nacional De Desarrollo - Plan Nacional Para El Buen Vivir 2013-2017. Secretaría Nacional de Planificación y Desarrollo, pp. 291-311.

Solow, R., M., 1957. Technical change and teh aggregate production function. The Review of Economics and Statistics 39, 312-320.

Stock, J.H., Yogo, M., 2005. Testing for Weak Instruments in Linear IV Regression, in Andrews, D.W.K., Stock, J.H. (Eds.), Identification and Inference for Econometric Models: Essays in Honor of Thomas Rothenberg. Cambridge University Press, Cambridge, pp. 80-108.

UNESCO-Institute for Statistics, 2011. UNESCO Data centre.

United Nations, 2013. ComeTrade Database.

Utterback, J., Abernathy, W., 1975. A Dynamic Model of Process and Product Innovation. Omega 3, 639-656.

Van Beveren, I., 2012. Total factor productivity estimation: A practical review. Journal of Economic Surveys 26 (1), 98-128.

Van der Wiel, H., Van Leeuwen, G., 2003. Do ICT spillovers matter? Evidence from Dutch firm-level data. CPB Netherlands Bureau for Economic Policy Analysis 26.

Vivarelli, M., 2014. Innovation, Employment and Skills in Advanced and Developing Countries: A Survey of Economic Literature. Journal of Economic Issues 48, 123-154.

Vivarelli, M., 2013. Technology, employment and skills: an interpretative framework. Eurasian Business Review 3, 66-89.

Wallsten, S.J., 2000. The Effects of Government-Industry R&D Programs on Private R&D: The Case of the Small Business Innovation Research Program. The Rand journal of economics 31, 82-100.

White, H., 1982. Maximum Likelihood Estimation of Misspecified Models. Econometrica 50, 1-25.

WIPO, INSEAD, 2011. Global Innovation Index 2011 Accelerating Growth and Development. INSEAD, France.

Wooldridge, J., 2010. Econometric Analysis of Cross Section and Panel Data. MIT Press.

Wooldridge, J., 2009. On estimating firm-level production function using proxy variables to control for unobsevables. Economics Letters 104, 112-114.

Zúñiga-Vicente, J.Á., Alonso-Borrego, C., Forcadell, F.J., Galán, J.I., 2014. Assessing the effect of public subsidies on firm R&D investment: A Survey. Journal of Economic Surveys 28, 36-67.

Zwick, T., 2006. The impact of training intensity on establishment productivity. Industrial relations: A journal of economy and society 45, 26-46.